UNIVERSITÉ DE MONTRÉAL

OPTIMISATION DE LA PLANIFICATION COURT-TERME D'UN SYSTÈME DE PRODUCTION HYDROÉLECTRIQUE DE GRANDE TAILLE

ALEXIA MARCHAND
DÉPARTEMENT DE MATHÉMATIQUES ET GÉNIE INDUSTRIEL
ÉCOLE POLYTECHNIQUE DE MONTRÉAL

THÈSE PRÉSENTÉE EN VUE DE L'OBTENTION
DU DIPLÔME DE PHILOSOPHIÆ DOCTOR
(MATHÉMATIQUES DE L'INGÉNIEUR)
SEPTEMBRE 2018

UNIVERSITÉ DE MONTRÉAL

ÉCOLE POLYTECHNIQUE DE MONTRÉAL

Cette thèse intitulée :

OPTIMISATION DE LA PLANIFICATION COURT-TERME D'UN SYSTÈME DE PRODUCTION HYDROÉLECTRIQUE DE GRANDE TAILLE

présentée par : MARCHAND Alexia
en vue de l'obtention du diplôme de : Philosophiæ Doctor
a été dûment acceptée par le jury d'examen constitué de :

M. LODI Andrea, Ph. D., président
M. GENDREAU Michel, Ph. D., membre et directeur de recherche
M. BLAIS Marko, M. Sc.A., membre et codirecteur de recherche
M. ANJOS Miguel F., Ph. D., membre
M. FRANGIONI Antonio, Ph. D., membre externe

REMERCIEMENTS

Je tiens tout d'abord à remercier Michel Gendreau et Marko Blais. Michel m'a accueillie au doctorat et a partagé avec moi sa grande expérience de la recherche. Marko m'a transmis son enthousiasme pour l'amélioration de la planification hydroélectrique et m'a guidée au quotidien.

Je tiens également à remercier Grégory Emiel pour son suivi du projet et ses suggestions très pertinentes, en particulier pour les deux premiers articles.

Merci aussi à Thérèse Falcon et Patrick Jeandroz pour m'avoir intégrée à l'unité Expertise Modélisation Mathématique (EMM), Direction de la Planification de la Production, Hydro-Québec Production. Je suis convaincue que cela m'a permis de mieux comprendre les enjeux réels de la planification de la production hydroélectrique, et que la pertinence de cette thèse en est grandement améliorée. Merci encore à Marko Blais et Grégory Emiel pour avoir passé énormément de temps à me former sur ces enjeux.

Merci également à Jonathan Guidi pour avoir mis en valeur les subtilités de la planification opérationnelle, ainsi que pour ses tests et ses commentaires sur les outils d'optimisation développés durant ce doctorat. Merci à Héliante Richard-Hamelin pour m'avoir aidée à rendre ces outils disponibles dans l'environnement de planification d'Hydro-Québec Production.

Merci à toute l'équipe EMM pour l'excellente ambiance de travail, et à l'équipe de boxe pour m'avoir bien défoulée !

Je tiens aussi à remercier mes parents, pour m'avoir soutenue pendant ces longues études et sans qui je ne serais pas arrivée là, et Mathieu, qui m'a supportée tout au long de ce doctorat.

Merci à la chaire de recherche industrielle CRSNG/Hydro-Québec en optimisation stochastique de la production d'électricité, à Hydro-Québec Production et au programme MITACS Accélération pour avoir financé ces travaux.

RÉSUMÉ

La planification de la production hydroélectrique vise à optimiser l'utilisation future d'un ensemble de centrales, afin de maximiser son efficacité tout en satisfaisant la charge électrique et de très nombreuses contraintes opérationnelles. A court terme, l'horizon étudié est typiquement de 7 à 15 jours au pas de temps horaire. Les décisions concernent l'état de fonctionnement de chaque groupe turbine-alternateur dans les centrales, les débits turbinés par les groupes en fonctionnement et les débits déversés par les ouvrages d'évacuation. Les contraintes opérationnelles se rapportent notamment à la sécurité des équipements et des personnes, à la fiabilité du système de production en énergie, en puissance et en transport, aux maintenances des équipements, aux transactions sur le marché de l'énergie et aux accords touristiques et environnementaux. Ces contraintes proviennent de très nombreux agents avec des objectifs parfois contradictoires.

Ce problème est complexe à résoudre, car il est combinatoire et de très grande taille. De plus, les vallées hydrauliques lient les décisions dans le temps et dans l'espace. Il existe de très nombreuses méthodes de résolution pour ce problème, mais aucune ne permet de résoudre des problèmes réels de grande taille dans des temps opérationnels. L'objectif de cette thèse est de développer des méthodes de résolution rapides et précises pour des systèmes de production de grande taille, comme celui d'Hydro-Québec. Afin de répondre à cet objectif, nous proposons trois modèles et méthodes de résolution qui exploitent la structure du problème de planification court-terme dans chacun de ses contextes d'utilisation.

La première méthode de résolution est dédiée aux analyses d'impact, qui permettent aux planificateurs d'évaluer le coût d'une décision de gestion. Les décisions évaluées sont par exemple des retraits d'équipement pour maintenance. La méthode de résolution doit fournir des solutions quasi optimales, ainsi qu'une mesure de la distance à la solution optimale. Nous avons donc développé un modèle de programmation linéaire en nombres entiers (PLNE) ainsi qu'une méthode de décomposition qui tire parti du petit nombre de contraintes liantes entre les vallées hydrauliques. Le système de production est partitionné en sous-systèmes géographiques, sans restriction sur la partition. La méthode de résolution est basée sur la relaxation lagrangienne et se déroule en trois phases. Tout d'abord, la relaxation linéaire est résolue, afin d'estimer la valeur duale des contraintes liant les sous-systèmes. Ensuite, les sous-problèmes de planification associés aux sous-systèmes sont résolus en conservant les variables entières. Enfin, le problème global est résolu en fixant les variables entières avec les résultats obtenus dans la résolution des sous-problèmes. De plus, la valeur de la relaxation linéaire

permet de calculer une borne sur l'écart à la solution optimale. Les résultats numériques montrent que notre méthode fournit des solutions extrêmement proches de l'optimum dans des temps opérationnels.

La deuxième méthode vise à ajuster rapidement un plan de production suite à une perturbation dans les intrants. L'objectif est ici de permettre aux planificateurs de valider rapidement la faisabilité du plan de production moyen-terme en considérant toutes les contraintes opérationnelles. Nous proposons un modèle mathématique précis et une méthode de résolution basée sur la recherche tabou. Afin de rendre la recherche efficace, nous avons développé de nouveaux voisinages larges qui exploitent les écarts entre l'offre et la demande, ainsi que la configuration des centrales dans les vallées. De plus, nous avons décomposé l'horizon par journée pour paralléliser la recherche tabou. Ce parallélisme permet de gérer de longs horizons, ce qui est essentiel pour attacher la planification court-terme aux décisions prises à moyen terme. Nous avons comparé notre méthode à un modèle de PLNE résolu avec un solveur générique. Même avec la solution initiale la plus naïve, notre recherche tabou parvient à des solutions proches de l'optimum dans des temps opérationnels, et jusqu'à 235 fois plus vite qu'un solveur générique.

La troisième méthode considère le processus opérationnel de planification court-terme à Hydro-Québec, qui a pour but de fournir des consignes de production aux répartiteurs. Afin de gérer l'incertitude sur les intrants, les planificateurs fournissent des règles de gestion plutôt qu'un plan de production. Nous avons donc développé une nouvelle forme de règles de gestion, adaptée aux vallées hydrauliques complexes et aux réservoirs très contraints. Ces règles sont évaluées sur un arbre de scénarios, représentant l'incertitude sur les apports en eau et la charge électrique. Nous avons optimisé l'ordre d'engagement des centrales défini dans ces règles à l'aide d'une recherche tabou. De plus, nous avons étudié la nécessité de prendre en compte cette incertitude dans l'optimisation. Les résultats numériques montrent que l'optimisation stochastique permet de réduire significativement la valeur objectif de la solution. Afin de répondre aux contraintes de temps opérationnelles, nous proposons une optimisation hybride : déterministe durant les premières itérations de la recherche tabou, puis stochastique. Cette méthode hybride permet d'améliorer la valeur objective moyenne de 10% lorsque les apports prévus sont moyens ou élevés.

ABSTRACT

Hydropower production planning aims at determining the future use of a set of hydro plants to maximize their efficiency, while satisfying the electrical load and a large number of operational constraints. At short-term, the horizon ranges from 7 to 15 days with hourly time steps. Decisions concern the operating status of each generating unit in hydro plants, the turbined flow in the functioning units, and the spilled flow in spillways. Operational constraints involve for instance safety of equipment and people, reliability of the production system, regulations on environment and tourism, equipment maintenance and transactions in the energy market. All these constraints are requests from many stakeholders with sometimes contradictory objectives.

The short-term hydropower production planning is hard to solve, because it is of large scale and combinatorial. Moreover, hydro-valleys link decision variables both in time and space. One can find many solution approaches in the literature, but they are not adapted to real-world large-scale production systems. The purpose of this thesis is to develop fast and accurate solution approaches for large-scale hydropower production systems, in particular Hydro-Québec's. We propose two new models and three new solution methods, which exploit the problem structure in each context of use.

The first approach is dedicated to impact analysis. Planners make this type of analysis to evaluate the cost of a given decision, for example the some equipment outage for maintenance. Therefore, the solution approach must provide near-optimal solutions and a measure of the gap to the optimum. We developed a new mixed-integer linear problem (MILP) and a new solution method. Our three-phase method approach exploits the small number of constraints between hydro valleys and is based on lagrangian decomposition. First, we solve the linear relaxation of the problem to estimate the dual value of the linking constraints. Then, the production system is partitioned into subsystems and the associated MILP subproblems are solved. Finally, the initial planning problem is solved with the commitment decisions fixed as in the subproblems solutions. Numerical experiments show that our solution approach leads to near-optimal solutions within operational computation time.

The second approach aims at quickly adjusting a given production planning after some perturbation in the data. Short-term planners will then be able to quickly validate the feasibility of the medium-term planning decisions while considering all operational constraints. We developed a new non-restrictive mathematical model and a solution method based on tabu search. To find good solutions quickly, we proposed new neighborhoods which consider the

current solution flexibility to satisfy the total load and reservoir volume bounds. Moreover, tabu search is performed in parallel for each day of the horizon. Hence, our approach can handle a long horizon. We compared our method with a classical MILP approach. Even with the most naive initial solution, our tabu search obtain solutions close to the optimum within operational time.

The third approach concerns the operational planning process from the short term to real time at Hydro-Québec. Short-term planners must provide daily instructions to real-time operators. To tackle uncertainty, planners provide operating rules instead of production schedules. We developed a new form of operating rules specially designed to handle large hydropower production systems with complex hydro-valleys and tightly bounded reservoirs. These rules are evaluated on a scenario tree, representing uncertain water inflows and electrical load, and optimized in a tabu search framework. We also evaluated the value of stochastic optimization for operating rules. Numerical results show that stochastic optimization has a significant value on scenarios with moderate or high inflows. However, it must be coupled with deterministic optimization to obtain good solutions when computational time is limited.

TABLE DES MATIÈRES

LISTE DES TABLEAUX

LISTE DES FIGURES

LISTE DES SIGLES ET ABRÉVIATIONS

HQP	Hydro-Québec Production
PLNE	Programmation linéaire en nombres entiers

CHAPITRE 1 INTRODUCTION

L'hydroélectricité représente 16 % de la production mondiale d'électricité (IEA, 2017), et plus de 99 % au Québec (Hydro-Québec, 2017). Cette source d'énergie est très intéressante, car elle est renouvelable et entraîne de faibles coûts d'exploitation. De plus, l'énergie potentielle de l'eau stockée dans les réservoirs permet de réguler la production hydroélectrique, grâce aux temps de démarrage et d'arrêt extrêmement faibles. La gestion des réservoirs doit cependant être planifiée pour assurer la fiabilité du parc de production en puissance et en énergie, et pour maximiser les profits engendrés par la production.

1.1 La planification de la production hydroélectrique

La planification de la production hydroélectrique vise à déterminer l'utilisation future d'un parc de production hydroélectrique, afin de répondre à la demande en électricité et de respecter les nombreuses contraintes opérationnelles au meilleur rendement possible. Ce problème étant très complexe à résoudre, les décisions sont prises en considérant différents horizons.

A long terme, c'est-à-dire pour les 5 prochaines années, les décisions concernent les investissements et renouvellements d'équipement, ainsi que les contrats bilatéraux sur le marché de l'énergie. Ces décisions se prennent à l'aide d'études ad hoc.

A moyen terme, c'est-à-dire en général pour les 1 à 2 prochaines années au pas de temps hebdomadaire, les planificateurs déterminent la trajectoire globale des volumes dans les réservoirs, ainsi que les principaux retraits d'équipement pour maintenance. Sur le marché, les volumes mensuels d'échanges sont fixés.

A court terme, c'est-à-dire pour les 7 à 15 prochains jours au pas horaire, il s'agit de décider des débits d'eau turbinés par les groupes turbine-alternateur de chaque centrale, ainsi que des débits déversés par chaque ouvrage d'évacuation. Les volumes de ventes sont ajustés, en fonction des prévisions de ventes aux enchères du jour pour le lendemain sur le marché "day-ahead".

A très court terme, c'est-à-dire pour la prochaine journée au pas horaires, les enchères sur le marché spot sont fixées et les productions des centrales sont ajustées afin de satisfaire les contraintes opérationnelles sur le réseau électrique.

Finalement, en temps réel, les répartiteurs fixent l'état de fonctionnement et la production de chaque groupe turbine-alternateur, ainsi que le débit déversé dans chaque ouvrage d'évacuation. Au niveau économique, les ventes correspondant aux enchères acceptées sur le marché spot doivent être satisfaites et les éventuels surplus de capacité peuvent être vendus.

On s'intéresse ici au problème de planification hydroélectrique à court-terme pour les systèmes de production de grande taille, en particulier celui d'Hydro-Québec. Cette société d'état est responsable de la production, du transport et de la distribution d'électricité au Québec. 99% de son électricité provient de centrales hydroélectriques. Son parc de production compte 63 centrales et 27 grands réservoirs, ce qui lui donne une capacité de stockage de 176 TWh et une puissance installée de 37 309 MW (Hydro-Québec, 2017).

1.2 Éléments de la problématique

Pour la planification court-terme de la production hydroélectrique, il est important de bien modéliser les fonctions de production, l'engagement des groupes, les différentes contraintes et l'incertitude dans les intrants.

1.2.1 Fonctions de production

Les centrales hydroélectriques sont composées d'un ou plusieurs groupes turbine-alternateur, qui transforment l'énergie mécanique de la chute d'eau en énergie électrique. L'eau est généralement dirigée du réservoir amont vers ces groupes à travers une ou plusieurs conduites communes, puis une conduite individuelle par groupe. De même, l'eau sortant des turbines poursuit son trajet dans des canaux de fuite, avant d'atteindre le segment de rivière aval.

Au niveau d'un groupe turbine-alternateur, l'électricité produite dépend du débit turbiné et de la hauteur de chute (c'est-à-dire la différence entre les niveaux amont et aval de la centrale) :

$$p = \rho.g.q.h.\eta(q) \tag{1.1}$$

où p est la puissance produite (MW), ρ est la masse volumique de l'eau (kg/m^3), g est l'accélération de la pesanteur (m/s^2), q est le débit turbiné (m^3/s), h est la hauteur de chute (m) et $\eta(q) < 1$ est le rendement du groupe au débit q.

La fonction de rendement du groupe est concave. On appelle débit *optimal* le point correspondant au rendement maximal. De plus, les groupes turbines-alternateurs sont conçus pour fonctionner sur une plage de débit déterminée. Il existe donc un débit *minimal* et un débit *maximal* de fonctionnement du groupe.

Au niveau de la centrale, il faut prendre en compte les pertes entraînées par le frottement et la turbulence dans les conduites en amont et en aval des groupes. De plus, selon le débit sortant du réservoir amont (turbiné et déversé) et la capacité d'évacuation à l'aval de la centrale, il peut se produire une accumulation d'eau à la sortie de la centrale. Cette augmentation du niveau aval de la centrale entraîne une réduction de la hauteur de chute ; c'est ce qu'on appelle l'effet de tarage aval. Cet effet a pour conséquence de créer une interdépendance entre les différents groupes turbine-alternateur d'une même centrale.

La production des centrales hydroélectriques est donc non linéaire, non convexe, non séparable et difficile à représenter dans un modèle mathématique.

1.2.2 Engagement des groupes turbine-alternateur

Le problème de planification court-terme peut être modélisé avec une variable binaire par groupe turbine-alternateur pour chaque pas de temps, représentant si le groupe est en fonctionnement ou non.

Pour un grand parc de production comme celui d'Hydro-Québec, il faut considérer le statut de plus de 150 groupes à chaque heure. Sur un horizon de 10 jours, cela représente 36 000 variables binaires. Nous sommes donc face à un problème combinatoire de très grande taille.

1.2.3 Contraintes

Comme tout problème dynamique, les variables de décisions sont fortement couplées dans le temps. De plus, les contraintes de satisfaction de la demande lient les variables des différentes centrales entre elles.

En outre, les planificateurs court-terme doivent concilier les requêtes de nombreux agents qui ont chacun des enjeux différents. Ces enjeux concernent notamment la sécurité des équipements, la fiabilité du système de production, les retraits pour maintenance, les réglementations, les transactions sur le marché de l'énergie, les accords environnementaux et touristiques. Les requêtes peuvent parfois mener à un problème irréalisable. Les planificateurs doivent alors trouver un compromis.

1.2.4 Incertitude dans les intrants

A court terme, il existe encore de l'incertitude sur les apports en eau dans les réservoirs, la demande électrique et la disponibilité des équipements.

1.2.5 Contexte de planification

A Hydro-Québec, les plans de production court-terme sont calculés dans trois contextes différents.

Le premier concerne les études et les analyses d'impact. Elles permettent par exemple d'évaluer la possiblité et le coût d'un retrait d'équipement pour maintenance.

Le deuxième est opérationnel par rapport au moyen-terme. L'objectif est de valider la réalisabilité des décisions prises à moyen-terme, en prenant en compte les contraintes opérationnelles du court-terme. L'horizon considéré est de 10 à 30 jours au pas horaire.

Le troisième est opérationnel par rapport au temps réel. Il s'agit ici de fournir des règles de gestion aux opérateurs pour le lendemain. L'horizon étudié est ici de 3 à 10 jours.

1.3 Objectifs de recherche

L'objectif de cette thèse est de trouver des modèles mathématiques et des méthodes de résolution adaptés à la planification court-terme des systèmes de production hydroélectrique de grande taille, en particulier celui d'Hydro-Québec. Les modèles doivent être suffisamment précis et les méthodes de résolution doivent fournir des solutions de bonne qualité dans des temps opérationnels. Nous avons décliné cet objectif général en trois sous-objectifs, selon le contexte de planification.

Le premier sous-objectif concerne le contexte d'étude. Pour évaluer correctement le coût d'une décision, l'outil de planification doit fournir des plans de production quasi-optimaux, ainsi qu'une distance de ces plans à la solution optimale. Nous cherchons donc une méthode de résolution basée sur les méthodes d'optimisation exacte, capable de fournir des solutions quasi-optimales et un saut de dualité très rapidement (moins de cinq minutes).

Le deuxième sous-objectif se rapporte à la validation du plan de production moyen-terme en considérant précisément l'ensemble des contraintes opérationnelles (notamment le réglage fréquence-puissance). Cette fois, ce n'est pas l'optimalité, mais la réalisabilité de la solution qui est importante. Le temps de calcul doit encore être extrêmement court (moins de cinq minutes).

Le troisième sous-objectif vise la planification opérationnelle de la production. Il s'agit de mettre en place une politique de gestion qui s'adapte aux aléas des prochains jours, et de l'optimiser en prenant en compte ces aléas. La représentation mathématique doit encore être très précise et le temps de calcul relativement court (moins d'une heure, étant donnée la dimension stochastique du problème).

1.4 Plan de la thèse

Le chapitre 2 présente une revue de littérature sur les différentes méthodes de résolution du problème de planification hydroélectrique à court terme. Le chapitre 3 décrit la démarche générale de la thèse et son organisation en trois articles. Ces articles sont exposés dans les chapitres 4, 5 et 6. Le chapitre 7 propose une synthèse de ces travaux. Finalement, la conclusion est présentée dans le chapitre 8.

CHAPITRE 2 REVUE DE LITTÉRATURE

Il existe un grand nombre de modèles et de méthodes de résolution pour le problème de planification hydroélectrique à court-terme. Les principales sont présentées et classifiées dans les revues de littérature de Labadie (2004), Vardanyan et Amelin (2011) et Osorio *et al.* (2013). van Ackooij *et al.* (2018) fait une revue de littérature très complète des modèles d'engagement de groupes. Taktak et D'Ambrosio (2017) recense les méthodes de résolution exactes, tandis que Saravanan *et al.* (2013a) étudie davantage les approches heuristiques et métaheuristiques.

On présente ici les différentes méthodes de résolution, selon la nature déterministe ou stochastique du problème.

2.1 Méthodes de résolution pour le problème déterministe

Les principales méthodes de résolution pour le problème déterministe sont la programmation linéaire, la programmation dynamique, la relaxation lagrangienne, la programmation linéaire en nombres entiers (PLNE) et les métaheuristiques.

La programmation linéaire et la programmation dynamique sont les méthodes de résolution classiques pour ce type de problèmes. La relaxation lagrangienne est très utilisée pour les problèmes de grande taille. La PLNE est devenue très compétitive avec l'essor des solveurs génériques. Enfin, les métaheuristiques sont actuellement très présentes dans la littérature.

2.1.1 Programmation linéaire

Jusqu'au début des années 2000, la programmation linéaire était une des méthodes les plus utilisées pour la planification de la production hydroélectrique (Labadie, 2004). Cette méthode a pour avantages de pouvoir résoudre des problèmes de grande taille et de donner un optimum global sans demander une solution initiale. En outre, l'implémentation est facile grâce aux nombreux solveurs génériques.

Par exemple, les méthodes des articles Johannesen *et al.* (1991), Piekutowski *et al.* (1993), Liang et Hsu (1996), Liang (1997) et Shawwash *et al.* (2000) utilisent la programmation linéaire.

Cependant, la programmation linéaire ne permet pas toujours de représenter avec précision le problème qui est non linéaire, ni de prendre en compte la nature discrète du problème d'engagement des groupes.

2.1.2 Programmation dynamique

La programmation dynamique, instiguée par Bellman et Dreyfus (1962), est une des méthodes classiques pour résoudre le problème de planification à court terme, en particulier pour l'engagement des groupes. La méthode demande simplement une discrétisation du temps et n'est pas restrictive dans la modélisation de l'objectif et des contraintes. Elle donne également une politique optimale pour chaque état du système.

Malheureusement, la méthode subit la *malédiction de la dimension* : le temps de calcul augmente de manière exponentielle avec le nombre d'états. De plus, les non-linéarités amplifient ce phénomène car elles nécessitent une discrétisation plus fine.

La méthode n'est en général pas directement exploitable pour des systèmes de taille réelle. On la combine donc à des heuristiques ou à des méthodes de décomposition qui réduisent le nombre d'états à explorer.

Entre autres, les articles de Ferreira (1992), Wang (2009), Cheng *et al.* (2009) et Pérez-Díaz *et al.* (2010) utilisent la programmation dynamique pour résoudre leur modèle de planification à court terme.

2.1.3 Relaxation lagrangienne

La relaxation lagrangienne (Lemaréchal, 2001) est aujourd'hui l'une des méthodes les plus performantes pour résoudre le problème d'engagement des groupes. Elle consiste à pénaliser certaines contraintes *liantes* avec des multiplicateurs de Lagrange dans l'objectif, de façon à décomposer le problème. On résout alors le problème dual en le décomposant en sous-problèmes indépendants, puis on recherche une solution réalisable (c'est-à-dire satisfaisant les contraintes liantes et celles d'intégrité).

Cette technique de résolution se prête bien au problème d'engagement des groupes, car si l'on relâche les contraintes globales (généralement la contrainte de demande), le problème se décompose par vallée (Dubost *et al.*, 2005).

Pour maximiser la fonction duale, les méthodes classiques sont celles de sous-gradients et celles de plans coupants. Ces deux méthodes ayant des problèmes de convergence, des méthodes plus avancées ont été développées, notamment les méthodes de faisceaux (Lemaréchal *et al.*, 1996; Bacaud *et al.*, 2001; Frangioni, 2002).

L'optimisation de la fonction duale donne généralement une solution fractionnaire. Pour obtenir une solution réalisable, on peut réoptimiser en ajoutant de nouvelles pénalités à la fonction objectif, comme dans la méthode de lagrangien augmenté de Belloni *et al.* (2003). On peut également utiliser des heuristiques, comme par exemple dans Dubost *et al.* (2005). Remarquons que cela ne donnera pas forcément la solution optimale.

La relaxation lagrangienne est très utile pour résoudre des instances de très grande taille, ou encore lorsque le temps de calcul est très limité, car elle peut fournir rapidement une solution de très bonne qualité (Frangioni *et al.*, 2011). De plus, il est possible de mesurer la qualité de cette solution grâce au saut de dualité. La relaxation lagrangienne s'est également révélée efficace pour des contraintes complexes, telles que les contraintes de rampes (Bhardwaj *et al.*, 2012).

Elle est très présente dans la littérature pour résoudre le problème d'engagement des groupes. Outre les articles déjà cités, on peut noter Pursimo *et al.* (1998); Finardi et da Silva (2006); Hechme-Doukopoulos *et al.* (2010) qui utilisent la relaxation lagrangienne dans un modèle, tandis que Borghetti *et al.* (2001); Takigawa *et al.* (2010) étudient les forces et les faiblesses de cette méthode.

Une autre méthode de décomposition classique est celle de Benders. Elle s'intéresse aux variables difficiles, c'est-à-dire celles qui, une fois fixées, rendent la résolution du problème facile. Elle a été appliquée au problème d'engagement des groupes (Liu *et al.*, 2010; Wu, 2013).

Le principal inconvénient de la relaxation lagrangienne, et des méthodes de décomposition en général, est la difficulté d'obtenir une solution réalisable. Comme on l'a vu, il faut réoptimiser le problème avec des techniques qui dépendent de la modélisation retenue. Par ailleurs, les sous-problèmes générés doivent pouvoir être résolus rapidement, par une méthode qui dépend encore du modèle. Ainsi ces méthodes manquent de flexibilité (Frangioni *et al.*, 2011).

2.1.4 Programmation linéaire en nombres entiers (PLNE)

La PLNE connaît un regain de popularité pour le problème d'engagement des groupes, grâce aux performances accrues des solveurs génériques.

La méthode nécessite un bon choix de linéarisation, des efforts de recherches sont faits dans ce sens actuellement (Frangioni *et al.*, 2009). Par ailleurs, il existe de nombreux solveurs génériques de PLNE, ce qui rend la résolution moins dépendante de la modélisation choisie.

En revanche, le temps de résolution est dépendant de la taille du parc et du niveau de détail donné. Celui-ci peut être long, généralement parce que les bornes inférieures obtenues sont de très mauvaise qualité (Frangioni *et al.*, 2011). On doit donc faire des choix dans la modélisation, ou bien coupler la méthode branch-and-bound avec des heuristiques pour accélérer la résolution (Parrilla et García-González, 2006).

De très nombreux modèles utilisent une formulation PLNE. On peut citer par exemple Christoforidis *et al.* (1996); Conejo *et al.* (2002); Borghetti *et al.* (2008); Diniz et Maceira (2008); Ge *et al.* (2014).

2.1.5 Métaheuristiques

Les revues de Farhat et El-Hawary (2009) et Saravanan *et al.* (2013b) répertorient plusieurs métaheuristiques pour la résolution du problème d'engagement des groupes, généralement des méthodes de population. On peut citer notamment le recuit simulé, la recherche tabou, les algorithmes génétiques, les réseaux de neurones et les essaims de particules.

A titre d'exemple, l'article de Simopoulos *et al.* (2006) utilise le recuit simulé pour la planification des groupes, et la répartition de la charge est traitée par programmation dynamique en prenant en compte des contraintes de rampes. Les articles de Yang *et al.* (2013) et Sampaio *et al.* (2013) utilisent des algorithmes génétiques. Les articles de Liang (2000) et Naresh et Sharma (2002) utilisent des réseaux de neurones artificiels. La méthode des essaims de particules et ses variantes sont assez populaires, on peut noter par exemple les articles de Fu *et al.* (2011) et Mahor et Rangnekar (2012).

Des heuristiques ont également été développées spécialement pour le problème d'engagement des groupes. La plus simple est sûrement la liste de priorités (Baldwin *et al.*, 1959), mais de nombreuses méthodes ont été élaborées. Par exemple, Ton-That *et al.* (2014) présente une heuristique de construction qui s'inspire de la programmation dynamique, en cherchant à garder le maximum de flexibilité dans les réservoirs (cette méthode était utilisée à Hydro-Québec au début de notre projet).

Ces méthodes sont attrayantes car elles sont simples à implémenter et peuvent gérer des contraintes complexes. En revanche, elles ne garantissent pas l'optimum global, tendent à converger trop vite vers un optimum local et nécessitent habituellement un paramétrage propre au système étudié. De plus, elles sont généralement gourmandes en mémoire et en temps de calcul. Les problèmes où elles sont appliquées ont presque toujours moins de 10 centrales et un horizon d'une journée.

Néanmoins, des méthodes simples et rapides comme la liste de priorités sont capables de fournir une solution initiale ou accélérer une méthode de résolution exacte. De plus, une méthode de recherche locale peut être rapide et efficace pour ajuster une solution (Dubost *et al.*, 2005; Ongsakul et Petcharaks, 2004; Seki *et al.*, 2010).

2.2 Méthodes de résolution pour le problème stochastique

Dans un modèle stochastique, l'information est révélée au fur et à mesure de l'horizon, contrairement à un modèle déterministe où tout est déjà connu dès le début de l'horizon. On appelle étapes les instants où l'on prend une décision.

La revue de littérature de van Ackooij *et al.* (2018) présente les différentes méthodes de résolution du problème d'engagement de groupes stochastique.

Les modèles stochastiques sont généralement classés en trois catégories, selon leur représentation de l'incertitude : l'optimisation stochastique (basée sur des scénarios), l'optimisation robuste et l'optimisation avec contraintes de probabilités.

2.2.1 Optimisation stochastique

Dans une méthode d'optimisation stochastique, l'incertitude est souvent représentée par un arbre de scénarios. On suppose que la première décision peut être prise avec certitude mais que les décisions futures sont aléatoires, ce qui donne un modèle stochastique à plusieurs étapes. La première décision sera véritablement opérationnelle, il faudra résoudre à nouveau le problème d'optimisation à partir de cette étape pour obtenir la décision optimale suivante, et ainsi de suite.

Les articles de García-González *et al.* (2007), Pousinho *et al.* (2011) et Fleten *et al.* (2011) considèrent des prix stochastiques. Le modèle de Fleten et Kristoffersen (2008) y ajoute des apports naturels stochastiques.

L'article de Vardanyan *et al.* (2013) compare l'incertitude entre les apports naturels et les prix : dans le contexte d'un petit producteur suédois, la variabilité des prix a plus d'impact que celle des apports naturels. Les articles de Fleten et Kristoffersen (2007) et Ladurantaye *et al.* (2009) comparent le modèle stochastique avec un modèle déterministe : naturellement, les solutions des modèles stochastiques sont plus robustes aux perturbations dans les intrants.

L'avantage des arbres de scénarios est la représentation explicite de l'incertitude : les distributions de probabilités sont discrétisées dans les noeuds de l'arbre. On peut donc convertir le problème stochastique en un problème déterministe équivalent de très grande taille, pour lequel les méthodes de décomposition sont bien adaptées.

Il existe deux façons classiques de décomposer le problème. La première consiste à relâcher les contraintes de non-anticipativité et de résoudre les sous-problèmes qui correspondent alors aux scénarios. Cela s'appelle la décomposition par scénario, une de ses variantes est le *progressive hedging* (Rockafellar et Wets, 1991; Carpentier *et al.*, 2013). La deuxième façon consiste à dualiser les contraintes d'équilibre entre l'offre et la demande, le problème se décompose alors par unité (Bacaud *et al.*, 2001; Carpentier *et al.*, 1996). On appelle cette méthode la décomposition spatiale, ou la décomposition par unité.

Une autre approche est la décomposition de Benders. D'après Cerisola *et al.* (2009), cette méthode est la plus efficace dans la plupart des cas. D'autres méthodes permettent d'obtenir une solution approchée sans décomposer, en distinguant les variables binaires des autres variables. On peut par exemple optimiser la production d'abord, puis prendre en compte l'engagement des groupes (Seguin *et al.*, 2016).

D'après van Ackooij *et al.* (2018), un inconvénient majeur des méthodes sur arbres de scénarios est qu'elles ne donnent que des résultats en probabilités. De plus, il est difficile de représenter précisément la distribution de probabilités dans l'arbre. Il existe cependant des méthodes évoluées de construction d'arbres pour prendre en compte cette difficulté (Dupačová *et al.*, 2003; Heitsch et Römisch, 2009).

2.2.2 Optimisation robuste

L'avantage de l'optimisation robuste est qu'elle permet de représenter l'incertitude de façon implicite, avec seulement des ensembles d'incertitude contre lesquels on se prémunit. Il n'est donc pas nécessaire de chercher une bonne représentation de l'incertitude.

Mais la solution peut être sous-optimale (c'est le *prix de la robustesse*) car on se prémunit contre tous les événements présents dans l'ensemble d'incertitude, sans tenir compte des probabilités. Ainsi, les événements rares ont le même poids que les autres. On peut contrôler un peu cet effet avec des paramètres tels que le *budget d'incertitude*, mais ils sont difficiles à paramétrer.

L'article de Mohammadi-ivatloo *et al.* (2013) présente un modèle robuste avec des prix aléatoires. L'article de Wu *et al.* (2012) compare des méthodes d'optimisation stochastique et d'optimisation robuste pour résoudre un problème d'engagement des groupes avec contraintes de sécurité (dans lequel la sécurité du système est la première priorité). La méthode d'optimisation robuste est rapide, mais elle est très dépendante du choix de l'intervalle. Au contraire, la solution par arbre de scénarios est stable par rapport au nombre de scénarios mais elle est lourde à calculer.

2.2.3 Optimisation avec contraintes de probabilités

L'idée des contraintes de probabilités est de fixer des probabilités de respect des bornes. Il y a deux façons de fixer ces probabilités sur les contraintes à respecter :

— individuellement, avec un seuil de probabilité par contrainte ;
— ou globalement, avec un seul seuil pour l'ensemble des contraintes.

La manière globale est naturellement la plus robuste, mais elle est plus difficile à calculer car elle lie davantage les variables entre elles.

Ce type de modèle est un compromis entre le coût et la robustesse. Il est proche de l'optimisation robuste, car intuitivement, l'ensemble d'incertitude correspond à une contrainte de probabilité. Les seuils de probabilité des contraintes représentent le niveau de risque accepté. Cependant, les contraintes de probabilité peuvent être non convexes et difficiles à évaluer, ce qui rend la résolution coûteuse.

L'article de van Ackooij *et al.* (2014) propose un modèle avec une contrainte de probabilité globale pour un problème avec apports naturels incertains, qu'il compare à un modèle avec contraintes de probabilités individuelles et un modèle robuste. Les deux alternatives demandent moins d'hypothèses sur les apports naturels et sont plus simples à calculer, mais elles donnent des résultats moins robustes que la méthode avec contrainte globale.

L'article de Zorgati et van Ackooij (2011) exhibe la difficulté de gérer à la fois l'aspect stochastique et l'aspect combinatoire de l'engagement des groupes. Il propose une formulation avec contrainte de probabilité globale, qu'il transforme dans une version avec contraintes individuelles afin de faciliter la résolution.

CHAPITRE 3 ORGANISATION DE LA THESE

Comme nous l'avons évoqué dans l'introduction, les plans de production court-terme sont calculés dans trois différents contextes de planification. Ces contextes présentent chacun des enjeux particuliers. Dans cette thèse, nous étudions différentes modélisations et méthodes de résolution du problème de planification hydroélectrique à court terme, adaptées à chacun des contextes de planification. Trois méthodes ont été développées et testées sur des instances réelles d'Hydro-Québec. Elles ont chacune mené à un article publié ou soumis dans une revue scientifique internationale. Ces articles sont présentés dans les chapitres 4, 5 et 6.

Le premier contexte de planification (présenté dans le premier article au chapitre 4) est l'analyse d'impact. Celle-ci vise à évaluer le coût d'une contrainte donnée, en calculant la différence des valeurs d'objectif entre un scénario qui prend en compte cette contrainte et un scénario qui l'ignore. Afin d'évaluer précisément le coût de cette contrainte, il est important que les solutions des scénarios soient (quasi) optimales. Ainsi, nous avons modélisé le problème de planification comme un PLNE et nous avons développé une nouvelle heuristique qui fournit rapidement des solutions quasi-optimales, ainsi qu'une borne supérieure sur l'écart à la solution optimale.

Le deuxième contexte de planification (présenté dans le deuxième article au chapitre 5) est la validation de la réalisabilité du plan moyen-terme. L'objectif de la planification est ici de chercher un plan de production qui suit les trajectoires de volume des grands réservoirs fournies par le plan moyen-terme, tout en satisfaisant l'ensemble des contraintes opérationnelles à court terme. Ces contraintes opérationnelles sont très nombreuses et souvent mises à jour (généralement plusieurs fois par jour). Nous proposons donc un modèle non linéaire réaliste, ainsi qu'une méthode de réoptimisation très rapide.

Le troisième contexte de planification (présenté dans le troisième article au chapitre 6) est le calcul de règles de gestion opérationnelles : chaque jour de la semaine, les planificateurs court-terme fournissent des règles aux répartiteurs, qui les appliqueront en temps réel à partir du lendemain. Ces règles sont ainsi valides durant un à trois jours. Or, certaines prévisions sont incertaines sur cet horizon, telles que les apports naturels aux réservoirs ou la charge électrique. Les règles de gestion doivent donc être robustes aux incertitudes. Nous avons modélisé les règles de gestion comme des macro-décisions, qui agissent sur les décisions d'un plan de production à l'aide d'un algorithme spécifique que nous avons développé. Nous proposons également une méthode d'optimisation de ces règles de gestion, ainsi qu'une extension qui prend en compte l'incertitude dans les prévisions d'apports et de charge électrique.

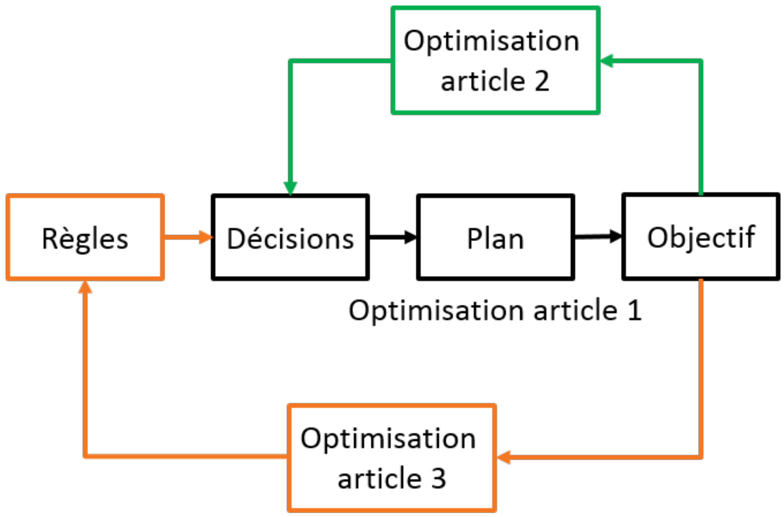

Figure 3.1 Méthodes d'optimisation utilisées dans les articles.

La figure 3.1 schématise les méthodes d'optimisation développées dans les articles pour chacun des contextes de planification.

Le premier article vise à développer une méthode de résolution adaptée aux analyses d'impact. Nous proposons une méthode de résolution qui fournit des solutions quasi-exactes dans des temps de calcul opérationnels, ainsi qu'une borne supérieure sur l'écart à la solution optimale. Le problème de planification est modélisé par un PLNE. Notre approche est basée sur la décomposition lagrangienne par les prix et exploite le petit nombre de contraintes liantes entre les vallées hydrauliques. Le système de production est partitionné en sous-systèmes (il n'y a pas de restriction sur la partition) et la résolution se déroule en trois phases. D'abord, le coût marginal des contraintes liantes est estimé en résolvant la relaxation linéaire du problème. Ensuite le problème est divisé en sous-problèmes, selon la partition du parc en sous-systèmes. Ces sous-problèmes sont des PLNE qui se résolvent rapidement avec une très bonne précision. La concaténation des solutions de ces sous-problèmes est une solution entière au problème global et est presque réalisable (à cause des contraintes liantes). Finalement, on résout le problème global en fixant le nombre de groupes engagés dans les centrales comme dans les solutions des sous-problèmes. Il devient alors un problème linéaire. La solution obtenue satisfait ainsi l'ensemble des contraintes du problème global, tout en restant proche de la solution des sous-problèmes. De plus, la valeur de la relaxation linéaire permet de calculer une borne supérieure sur l'écart à la solution optimale. Cet article a été publié dans le journal *IEEE Transactions on Power Systems* (Marchand *et al.*, 2018b).

Le deuxième article propose une méthode d'ajustement rapide d'un plan de production. L'objectif est ici de permettre aux planificateurs de valider rapidement la faisabilité du plan de production moyen-terme en prenant en compte toutes les contraintes opérationnelles. Par rapport au premier article, les fonctions de production sont modélisées plus précisément et le système de réglage fréquence-puissance est représenté (il force un sous-ensemble des centrales à avoir le même régime de production en tout temps). Nous présentons un modèle mathématique capable de gérer les requêtes parfois contradictoires des différents acteurs de la planification court-terme. Le problème est résolu à l'aide d'une recherche tabou qui exploite la structure du problème. De nouveaux voisinages larges sont proposés : ils incluent des modifications sur de longues périodes et prennent en compte les écarts entre l'offre et la demande dans la solution courante. De plus, la recherche est parallélisable sur chaque jour de l'horizon, ce qui la rend extensible à de très longs horizons. Notre approche est comparée à la résolution d'un PLNE avec un solveur générique, en termes de précision et de temps de calcul. Cet article a été soumis au journal *Journal of Water Resources Planning and Management* (Marchand *et al.*, 2018a).

Le troisième article concerne le processus de planification court-terme/temps-réel. L'objectif est de trouver une politique de gestion utilisable en temps réel. Cette politique doit prendre en compte l'incertitude dans les données, notamment la demande électrique et les apports naturels dans les réservoirs. Nous proposons alors des règles de gestion adaptées à la production hydroélectrique, ainsi qu'une méthode d'optimisation de ces règles. L'incertitude est représentée par un peigne de scénarios, ce qui est ici suffisant car la simulation des règles n'est pas anticipative. Les règles sont optimisées à l'aide d'une recherche tabou intégrée dans une recherche à voisinages variables. La pertinence de la prise en compte de l'incertitude est évaluée sur des scénarios réels, répartis sur les différentes saisons de l'année. Cet article a été soumis au journal *Computational Management Science* (Marchand *et al.*, 2018c).

Les PLNE présentés dans les deux premiers articles ont été résolus avec le solveur générique CPLEX (CPLEX, 2017). De nombreuses combinaisons de paramètres de résolution ont été testés et le meilleur paramétrage a permis de réduire considérablement le temps de calcul pour notre genre de problème, d'un facteur de 10 à 100. Etant donné le nombre conséquent de paramètres, nous trouvons utile de nommer ici ceux qui ont eu le plus d'influence sur le temps de calcul :

— les problèmes linéaires, ainsi que le noeud racine de l'arbre de "branch-and-bound", sont résolus à l'aide de l'algorithme barrière ;
— l'arbre de "branch-and-bound" est exploré en profondeur d'abord ;
— les coupes sont toutes désactivées.

CHAPITRE 4 ARTICLE 1: FAST NEAR-OPTIMAL HEURISTIC FOR THE SHORT-TERM HYDROGENERATION PLANNING PROBLEM

Alexia Marchand[1,2,3], Michel Gendreau[1,2], Marko Blais[3] et Grégory Emiel[3]

[1]CIRRELT, Montréal, Québec, Canada.

[2]Département of Mathematics and Industrial Engineering, Polytechnique Montréal, Montréal, Québec, Canada.

[3]Hydro-Québec, Montréal, Québec, Canada.

Cet article a été publié le 24 avril 2017 dans la revue *IEEE Transactions on Power Systems*.

Abstract Short-term hydro-generation planning can be efficiently modeled as a mixed integer linear program (MILP). Depending on the size of the system and the time horizon, the resulting MILP may be too large to be solved in reasonable time with commercial solvers. This paper presents a three-phase approach based on price decomposition that yields quickly near-optimal solutions to large-scale real-world instances. For any partition of the production system into subsystems, the first phase solves a linear program (LP) to estimate the marginal cost of electricity in each subsystem. The second phase solves local MILPs corresponding to each subsystem, and gives a solution that is almost feasible. The final phase slightly perturbs the solution to obtain a feasible solution that is proven to be near-optimal. Our method is tested on real instances corresponding to Hydro-Québec's production system.

Keywords Hydro unit commitment, price decomposition, near-optimal heuristic, combinatorial problem.

Nomenclature

The following notation is used throughout the paper.

Indexes and sets:

$t \in \{1, 2, ..., T\}$	Ordered set of time periods [h].
$r \in R$	Set of reservoirs.
$s \in S$	Set of river sections.
$d \in D$	Set of spillways.
$c \in C$	Set of hydroelectric power plants.
$k \in K_{c,t}$	Set of possible configurations of hydro power plant c at period t.
$z \in Z$	Set of electrical zones.
$l \in L$	Set of electrical (oriented) links.
S_r^{up}, S_r^{dn}	Set of river sections directly upstream and downstream of reservoir r.
C_s, D_s	Sets of hydro power plants and spillways directly upstream of river section s.
r_c, s_c	Reservoir upstream and river section downstream of hydro power plant c.
E_z	Set of hydro plants connected to electrical zone z.
L_z^{in}, L_z^{out}	Sets of electrical links incoming to and outgoing from electrical zone z.

Parameters:

$\eta_{r,t}$	Natural inflows of reservoir r during period t [m^3/s].
ω_r	Final value of water at reservoir r [MWh/hm^3].
τ_s	Maximum time for upcoming water to run down river section s [h].
$\alpha_{s,t'}$	Proportion of upcoming water that reaches the end of river section s after t' periods ($\sum_{t'=0}^{\tau_s} \alpha_{s,t'} = 1$).
γ_k	Maximum power output of configuration k [MW].
$\delta_{z,t}$	Electrical load to be satisfied in zone z during period t [MW].
ρ_t	Operational reserve at period t [MW].
θ	Penalty term for variations of turbined flow [MWh/(m^3/s)].
ζ	Conversion factor from water flow [m^3/s] to volume [hm^3] during a period, $= 0.0036$.

Decision variables:

$\mathbf{v}_{r,t}$	Volume of reservoir r at the end of period t [hm^3].
$\mathbf{f}_{s,t}$	Volume in transit in river section s at the end of period t [hm^3].
$\mathbf{u}_{s,t}$	Water flow upcoming to river section s during period t [m^3/s].
$\mathbf{o}_{s,t}$	Water flow outgoing from river section s during period t [m^3/s].
$\mathbf{w}_{d,t}$	Spilled water at spillway d during period t [m^3/s].
$\mathbf{q}_{c,t}$	Turbined water at hydro plant c during period t [hm^3].
$\mathbf{h}_{c,t}$	Water head at hydro plant c during period t (m).
$\mathbf{p}_{c,t}$	Power output at hydro plant c during period t [MW].
$\mathbf{g}_{k,c,t}$	Power output of hydro plant configuration k at hydro plant c during period t [MW].
$\mathbf{x}_{k,c,t}$	Equals 1 if configuration k of hydro plant c is chosen at period t , 0 otherwise.
$\mathbf{b}_{l,t}$	Power transmitted through electrical link l during period t [MW].

Functions:

$\Phi_r(.)$	Water level of reservoir r [m]. Piecewise concave linear function of $\mathbf{v}_{r,t}$.
$\Pi_k(.)$	Production function of configuration k at hydro plant c and period t [MW]. Polyhedral function of $\mathbf{x}_{k,c,t}$, $\mathbf{q}_{c,t}$ and $\mathbf{h}_{c,t}$.
$\Psi_s(.)$	Upstream water level of river section s [m]. Linear function of $\mathbf{f}_{s,t}$ and $\mathbf{u}_{s,t}$.
$\Xi_l(.)$	Power loss through electrical link l. Linear function of $\mathbf{b}_{l,t}$.
$\lvert.\rvert$	Absolute value function.

4.1 Introduction

4.1.1 Short-term hydro-generation scheduling

Production planning of a large hydro-generation system requires taking different decisions on different horizons. In the long term, i.e., typically for the next 5 years, decisions involve investments in new projects and major maintenance, as well as commitments in long-term bilateral contracts. In the medium term, i.e., usually for the next 2 years, the planning is reviewed on a weekly basis. Decisions aim at optimally balancing the energy between the main reservoirs, scheduling the main outages and financially hedging on the market. In the short term, i.e., for periods between 7 and 15 days on a hourly basis, the planners adapt the medium-term decisions (given at the hydro plants level) to the generating units level. Finally, in the very short term, i.e., for the next day on a hourly basis, an operational planning of hydro plants is produced and transactions are made on the spot market.

Short-term hydro scheduling aims at validating the medium-term targets, quantifying the impacts of outages modifications, and providing instructions to the daily planners. It is also used for evaluating the hydraulic risk (regarding security, environment, and unnecessary spillage), and for sensitivity analysis on various input scenarios. The decisions to be taken at each hour are the unit commitment, the turbine discharge at each hydro plant and the spill discharge at each reservoir. This problem is combinatorial, coupled in time and space, and, usually, quite large. Consequently, solving the short-term hydro-generation scheduling problem on a large production system may be very hard with direct approaches and standard commercial solvers.

Our work is motivated by the situation of Hydro-Québec Production (HQP), the business unit responsible for managing the hydro-generation assets of Hydro-Québec, a government-owned public utility that generates, transmits and distributes electricity in Québec, Canada. 99% of its generated power is from hydroelectric source, and it is one of the largest hydro producers in the world, with an installed capacity of 36 912 MW and a storage capacity of 176 TWh (in 2015) (Hydro-Québec, 2015).

The production system is very large and complex: it is composed of 12 hydro valleys, with 27 large reservoirs and 63 hydro plants. Transmission complexity is increased by the huge distances between production sites (in the North and North-East) and load (in the South). As a result, HQP's short-term scheduling problem is of very large scale: a 10-day planning involves around 650 000 variables, 42 000 binaries and 370 000 constraints. Consequently, it is very hard to solve with direct approaches and standard commercial solvers.

Currently, Hydro-Québec planners tackle that problem with a heuristic based on resource decomposition and rule-based strategies (Ton-That *et al.*, 2014). It is fast, but not adapted to impact analysis since it does not give any guarantee on optimality. Furthermore, it is not easily adapted to the production system evolution or to unusual situations.

Given the operational context, an efficient solution method must obtain a good solution quickly ($<$ 5 minutes), be flexible enough to integrate user constraints, and give a measure of the solution quality, i.e., a bound on the optimal solution.

4.1.2 Existing approaches in the literature and industry

Several short-term hydro-generation models already exist for large-scale production systems, see Labadie (2004); Vardanyan et Amelin (2011); Bhardwaj *et al.* (2012); Osorio *et al.* (2013); Tahanan *et al.* (2015); Taktak et D'Ambrosio (2017) and references therein. For example, Tahanan *et al.* (2015) is a rather complete literature review on large-scale unit-commitment problems, and Taktak et D'Ambrosio (2017) presents different approaches used for some of the largest real-world production systems. For large-scale problems, most of the solution methods are based on decomposition approaches, especially Lagrangian relaxation (Belloni *et al.*, 2003; Dubost *et al.*, 2005; Finardi et da Silva, 2006; Hechme-Doukopoulos *et al.*, 2010; Seki *et al.*, 2010; Kargarian *et al.*, 2015) and Benders decomposition (Liu *et al.*, 2010; Wu, 2013). They are able to handle complex instances and to give good solutions quickly. However, it is often still a challenging task to solve the subproblems and to recover the primal feasibility of the solution. Primal recovery can be done either by reoptimization (Belloni *et al.*, 2003; Hechme-Doukopoulos *et al.*, 2010) or with heuristics (Dubost *et al.*, 2005; Seki *et al.*, 2010). The approaches presented in Belloni *et al.* (2003); Dubost *et al.* (2005); Finardi et da Silva (2006); Kargarian *et al.* (2015) have been designed for real-world problems.

On the other hand, generic solvers (CPLEX, 2015; Gurobi, 2015) have improved and can now handle large-scale mixed integer linear programs (MILP) (Christoforidis *et al.*, 1996; Borghetti *et al.*, 2008; Diniz et Maceira, 2008; Ge *et al.*, 2014). They are not dependent on the structure of the problem and they usually find good solutions quickly (Frangioni *et al.*, 2011). They can even obtain solutions at any desired precision level, at the cost of higher solution times. To shorten solution times, specialized heuristics have been developed. For instance, Frangioni *et al.* (2011) proposes to primarily solve Lagrangian relaxation to improve the bounds for branch-and-bound. The authors in Parrilla et García-González (2006) use the special structure of the problem to reduce the size of their MILP as much as possible. Other approaches have been used for short-term generation scheduling, such as linear programming (Shawwash *et al.*, 2000), dynamic programming (Pérez-Díaz *et al.*, 2010), nonlinear programming (Seguin *et al.*, 2016) and heuristic methods (Saravanan *et al.*, 2013b; Gil *et al.*, 2003).

Also, stochastic versions of the unit commitment problem have been studied, especially with uncertainty on natural inflows and prices (Vardanyan *et al.*, 2013). See Tahanan *et al.* (2015) and Zheng *et al.* (2015) for more details.

Models coupling unit commitment with other issues, such as selling energy or deregulated markets, have also been considered (see, e.g. Fosso *et al.* (1999); Maceira *et al.* (2002)).

This paper presents a MILP formulation of the problem and a new solution method that takes advantage of both MILP and Lagrangian decomposition. Given any partition of the production system, our method is able to quickly provide a satisfying solution in three phases. During the first phase, the marginal costs of the constraints linking the subsystems are estimated by solving the linear relaxation of the global problem. In the second phase, the linking constraints are dualized and the problem is decomposed w.r.t. the subsystems. The subproblems are smaller, less constrained, and independent, hence they can be solved quickly in parallel. The solutions of the subproblems form a near-feasible optimal solution, which is rapidly repaired in the third phase via a linear program.

For real-world large-scale instances of the short-term hydro scheduling problem, our novel approach can find near-optimal solutions much faster than generic solvers or the previously cited methods, with negligible losses in optimality. It is easy to implement and to adapt, with its MILP formulation and its independence of the production system partition.

The paper is organized as follows. In Section II, we present a mathematical modeling of the short-term planning problem at Hydro-Québec. In Section III, we present our decomposition method. Then in Section IV, we test our approach on some real instances and we compare it with the current heuristic used at Hydro-Québec and with generic solvers. Finally, some conclusions are drawn in the last section.

4.2 Mathematical Modeling

The Hydro-Québec production system is modeled with a hydraulic network and an electrical one. With the definitions presented in the Nomenclature section, we will describe the main modeling choices and then give a mathematical formulation of Hydro-Québec's short-term planning problem.

4.2.1 Modeling choices

Hydraulic topology

In the hydraulic network, each reservoir feeds a set of hydro plants and spillways, and each hydro plant or spillway is connected to a unique downstream river section. Each river section leads to a downstream reservoir. With this representation, reservoirs may have several downstream river sections, and several downstream reservoirs. Reservoirs may also have more than one upstream river section. Fig. 4.1 shows an example of reservoir with several downstream river sections. Reservoir r_0 has one downstream hydro plant c_1, and two downstream spillways d_1 and d_2. c_1 and d_1 are connected to river section s_1, whereas d_2 is connected to river section s_2. s_1 and s_2 are respectively connected to the reservoirs r_1 and r_2.

A MILP model

We model our problem as a MILP, in order to take advantage of the good performance of the generic solvers that are available commercially. For the production functions and the expressions of the water level, piecewise linear approximations are accurate enough and

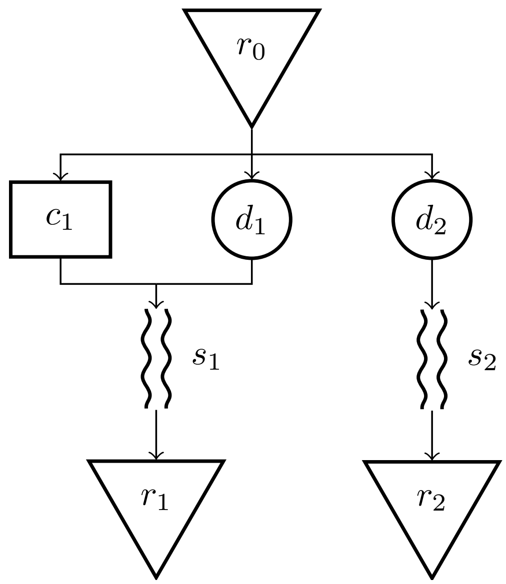

Figure 4.1 Example of a reservoir with several downstream river sections.

simplify the solution, especially for a large-scale system (Shawwash *et al.*, 2000; Dubost *et al.*, 2005).

Commitment decisions

An intuitive modeling of the commitment decisions would consider one binary variable per generating unit and time period (Dubost *et al.*, 2005). However, this implies a huge number of possible configurations of committed units per hydro plant and time period, which grows exponentially with the number of available units in the hydro plants. Moreover, units within a hydro plant are usually very similar, so a very large proportion of the possible configurations are redundant, creating a lot of symmetry in the problem (Seguin *et al.*, 2016).

In our context, short-term scheduling tackles a time-horizon of 10 to 30 days with hourly time steps. It is not aimed at providing an operational plan, but is rather used for impact analysis and scenario comparisons. It is thus precise enough to only consider the *number* of committed units per hydro plant and time period. Consequently we only consider $(n + 1)$ binary configuration variables per hydro plant and time period, where n is the number of available units in the plant (Shawwash *et al.*, 2000). Each one of these variables corresponds to the commitment of a given number of units. This assumption reduces drastically the number of possible choices (and the symmetry).

For each number of committed units, in a given hydro plant and at a given time period, we precalculate the best configuration of committed units. In our case, we choose the most efficient configuration via an inhouse program for optimal unit loading based on Breton *et al.* (2002).

Besides, in order to avoid premature aging of the equipment (Bakken et Bjorkvoll, 2002), we limit unit startups and shutdowns. Rather than using the standard startup and shutdown costs, we penalize the variations of turbined flow in each plant. That penalization choice accelerates the MILP solving time by limiting the impact of the binary variables on the objective.

Production functions

For each configuration (i.e., number of committed units) of hydro plant and each time step, we approximate the generated power as a polyhedral function of the turbined flow in the hydro plant and the water head. That function is piecewise linear w.r.t. the turbined flow and linear w.r.t. the water head (Diniz et Maceira, 2008; Carpentier *et al.*, 2015). The tailrace effects are taken into account in the calculation of the production functions.

Fig. 4.2 illustrates the generated power of a real plant configuration and of a real hydro plant with 3 available units. The bullets correspond to the extreme points of the production functions in the model, whereas the dashed lines represent the real values. Fig. 4.2(a) shows the production function for a chosen plant configuration. Two curves are drawn, depending on the extreme values of water head. Fig. 4.2(b) represents four different curves of generated power in a hydro plant depending on the unit configurations, for a fixed water head. We can see that the piecewise approximation of the power output w.r.t. the turbined outflow is accurate enough, since the curvature of the real values between the points is extremely low.

Electricity transmission

The electrical network is modeled as an oriented graph, where each node is called an electrical zone and is associated to a set of hydro plants. Therefore the production of a zone is the total production of its associated plants. Power can be transmitted along the arcs (links), only in the directions of the links: Hydro-Québec's network can be considered radial. Power transit in a link may be affected by losses; they are modeled as a linear function of the power transmitted through the link. In addition, to ensure the stability and the reliability of the transmission network, we take into account operational reserve constraints (Dubost *et al.*, 2005).

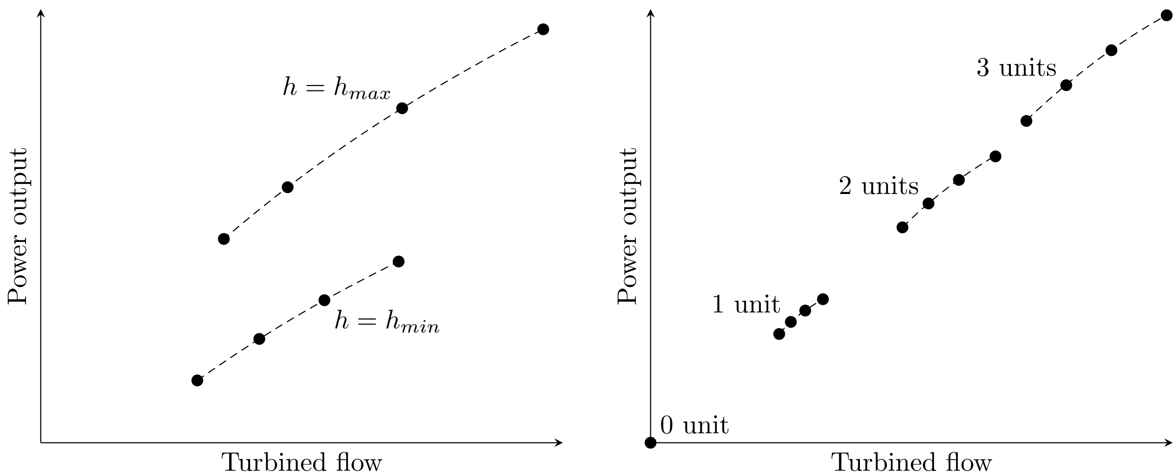

Figure 4.2 Production functions. (a) Unit configuration. (b) Hydro plant with 3 available units (fixed water head).

4.2.2 Mathematical formulation

The purpose of the short-term planning problem is to satisfy the operational constraints as efficiently as possible. Thus the main objective is to maximize the value of water stored in the reservoirs at the end of the horizon. The value of water is estimated by the medium-term model for each reservoir.

Considering the modeling choices made in the previous section, the mathematical model can be written as follows.

Maximize the final value of water and penalize variations of turbined flow:

$$\max \sum_{r \in R} \omega_r . (\mathbf{v}_{r,T} + \sum_{s \in S_r^{up}} \mathbf{f}_{s,T}) - \sum_{c \in C} \sum_{t=1}^{T} \theta . |\mathbf{q}_{c,t} - \mathbf{q}_{c,t-1}| \tag{4.1}$$

subject to:

$$\mathbf{v}_{r,t} = \mathbf{v}_{r,t-1} + \zeta.\eta_{r,t} + \sum_{s \in S_r^{up}} \zeta.\mathbf{o}_{s,t} - \sum_{s \in S_r^{dn}} \zeta.\mathbf{u}_{s,t} \qquad \forall r, \forall t \qquad (4.2)$$

$$\mathbf{u}_{s,t} = \sum_{c \in C_s} \mathbf{q}_{c,t} + \sum_{d \in D_s} \mathbf{w}_{d,t} \qquad \forall s, \forall t \qquad (4.3)$$

$$\mathbf{o}_{s,t} = \sum_{t'=0}^{\tau_s} \alpha_{s,t'}.\mathbf{u}_{s,t-t'} \qquad \forall s, \forall t \qquad (4.4)$$

$$\mathbf{f}_{s,t} = \mathbf{f}_{s,t-1} + \zeta.\mathbf{u}_{s,t} - \zeta.\mathbf{o}_{s,t} \qquad \forall s, \forall t \qquad (4.5)$$

$$\mathbf{h}_{c,t} = \Phi_{r_c}(\mathbf{v}_{r_c,t}) - \Psi_{s_c}(\mathbf{f}_{s_c,t}, \mathbf{u}_{s_c,t}) \qquad \forall c, \forall t \qquad (4.6)$$

$$\sum_{k \in K_{c,t}} \mathbf{x}_{k,c,t} = 1 \qquad \forall c, \forall t \qquad (4.7)$$

$$\mathbf{p}_{c,t} = \sum_{k \in K_{c,t}} \mathbf{g}_{k,c,t} \qquad \forall c, \forall t \qquad (4.8)$$

$$\mathbf{g}_{k,c,t} = \Pi_k(\mathbf{x}_{k,c,t}, \mathbf{q}_{c,t}, \mathbf{h}_{c,t}) \qquad \forall c, \forall t, \forall k \in K_{c,t} \qquad (4.9)$$

$$\delta_{z,t} = \sum_{c \in E_z} \mathbf{p}_{c,t} + \sum_{l \in L_z^{in}} (\mathbf{b}_{l,t} - \Xi_l(\mathbf{b}_{l,t})) - \sum_{l \in L_z^{out}} \mathbf{b}_{l,t} \qquad \forall z, \forall t \qquad (4.10)$$

$$\sum_{c \in C} \sum_{k \in K_{c,t}} \gamma_k.\mathbf{x}_{k,c,t} \geq \sum_{z \in Z} \delta_{z,t} + \rho_t \qquad \forall t \qquad (4.11)$$

$$\mathbf{x}_{k,c,t} \in \{0, 1\} \qquad \forall c, \forall t, \forall k \in K_{c,t} \qquad (4.12)$$

Eq. (4.2) ensures the conservation of water in the reservoirs. Eq. (4.3) and Eq. (4.4) respectively define what comes in and out of the rivers sections at each time step, considering possible delays. Eq. (4.5) defines the volume in transit in the river sections. Eq. (4.6) defines the water heads of the hydro plants: the level of the upstream reservoir minus the level at the beginning of the downstream river section. Eq. (4.7) permits only one configuration for each hydro plant and time period. Eq. (4.8) and Eq. (4.9) define the production of each hydro plant as the sum of the productions of its possible configurations, where the production of a configuration is a polyhedral function of the turbined flow and the water head if the configuration is chosen, zero otherwise. Eq. (4.10) ensures the conservation of energy in the electrical network. Eq. (4.11) expresses the operational reserves requirements.

All variables take non-negative values and are bounded. The configuration choices $\mathbf{x}_{k,c,t}$ are binary, as in Eq. (4.12).

4.3 Method

4.3.1 Aims and motivation

As explained in Section 4.1, the solution method must be fast to be used in daily planning, and precise enough to allow for impact analysis and scenario comparisons. Directly solving the problem with a commercial solver has first been tested, and it could not meet these requirements: even with heavy parameter tuning, the solution time of a 10-day planning is no less than 1.5 hours on high-performance computational servers.

To be effective, the solution method needs to exploit the characteristics of the model. There are few linking constraints between the hydro valleys: the load and operational reserves. Consequently, price decomposition appears a good solution approach (Finardi et Scuzziato, 2014). Moreover, the objective is very flat, since switching the number of committed units between two hydro plants during an hour is almost insignificant for the final value of water. Hence, we expect a very small integrality gap, and a method based on Lagrangian relaxation should be efficient.

4.3.2 Principle of the method

Our method relies on the well-known "divide-to-conquer" idea (Sagastizábal, 2012). The production system is divided into subsets of hydro plants, and each subsystem is solved individually.

In order to partition in subsystems, we need to relax the linking constraints: define the electrical zones and the river sections that form the borders, remove the flow conservation constraints of Eq. (4.2) on the reservoirs downstream the river sections and Eq. (4.10) on the electrical zones, as well as the operational reserves constraints of Eq. (4.11). As in Lagrangian relaxation, these constraints are transformed into penalties in the objective, where their costs correspond to their dual values.

Thus each subsystem is independent and tries to maximize its profit by producing energy, and by exchanging water and energy with the adjacent subsystems. The costs of water and energy are the dual values of the linking constraints.

Fig. 4.3 shows an example of decomposition on a small production system. The hydraulic network is represented with thick boxes for the plants and thick arrows for the river sections. The circles symbolize the electrical zones and the thin arrows represent the electrical links. Fig. 4.3(a) shows a possible partition in three subsystems. In this case, the borders are constituted by two electrical zones and one river section, their marginal costs are the dual

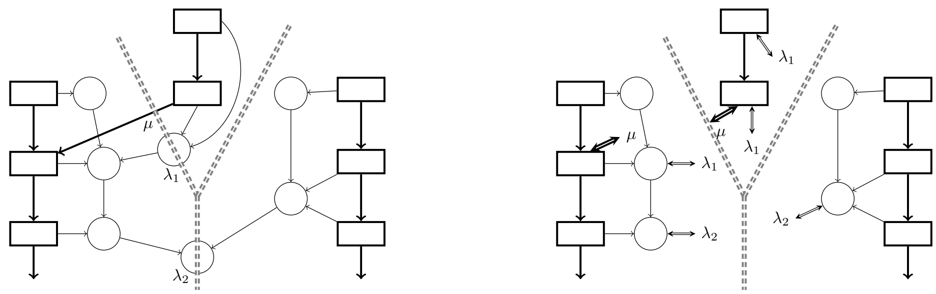

Figure 4.3 Example of decomposition of a production system. (a) Partition. (b) Subsystems and exchanges.

values of the flow conservation constraints. Fig. 4.3(b) represents the subsystems as they are seen after decomposition. The borders are removed and the new exchanges are illustrated by double arrows with their corresponding marginal costs (for the sake of simplicity, dualization of the reserve constraints is not represented).

According to Lagrangian relaxation, if the model did not have any binary variable, that kind of decomposition would lead to a primal solution that would be optimal, but not necessarily feasible because the linking constraints may not be satisfied. In our case, we expect the integrality gap to be very small, so the integrality of the primal solution should have a very small effect on this result. Thus we expect an integer primal solution that is near optimal and almost feasible (except for the linking constraints). We will then have to “repair” that integer solution, to make it totally feasible.

Hence the general structure of the method is the following:

1. Estimate the dual values of the linking constraints;
2. Solve each subsystem individually;
3. Repair the solution given by the decomposition.

4.3.3 Description of the method

Estimation of the marginal costs

The method estimates the marginal costs by calculating the optimal dual values of the linking constraints of Eq. (4.2), Eq. (4.10) and Eq. (4.11) in the convexified problem, i.e., without the integrality constraints.

The convexified problem is linear and can be solved in reasonable time on a heavily tuned generic solver (good tuning permits to divide the solution time by a factor of 10 to 100). The solution also gives us an upper bound on the objective.

In order to reduce the search space and reach good computational times, the configurations are then filtered. For each hydro plant and time period, only the configurations permitting the turbined outflow or the generated power given by the convexified solution are allowed for the rest of the solution process (if the value of turbined outflow or generated power is infeasible, the two nearest configurations are also allowed).

Thus, the following constraint is added to the model:

$$\sum_{c \in C} \sum_{t=1}^{T} \sum_{k \notin K_{c,t}^{filt}} \mathbf{x}_{k,c,t} = 0 \tag{4.13}$$

where $K_{c,t}^{filt}$ is the set of allowed configurations of hydro plant c at period t, according to the filter above.

In the convexified solution, the variables $\mathbf{x}_{k,c,t}$ corresponding to the choices of the eliminated configurations may be non-zero. For this reason, the convexified problem is solved a second time with this extra constraint. The marginal values of the second solution are more accurate (usually slightly higher) and they will help building faster an integer solution which is closer to the linking constraints.

Solving the subsystems

The production system is divided into subsystems. Each subsystem contains a (possibly empty) subset of hydro plants and the associated hydraulic and electrical subgraphs defined by the borders.

We now solve a MILP that only considers the constraints Eq. (4.2)-(4.10) and Eq. (4.12) in the interior of the subsystems, and the penalties of the linking constraints Eq. (4.2), Eq. (4.10), Eq. (4.11) at the borders. The penalty costs are the dual values calculated in the first phase.

Thus, the subsystems are independent and the spatial coupling has been reduced a lot. Moreover, the demand and reserve constraints do not need to be satisfied exactly anymore, hence we just have a revenue-maximization problem. That problem is composed of independent subproblems: one small MILP for each subsystem.

Considering BS and BZ as the sets of river sections and electrical zones defining the borders of the subsystems, and a subsystem i, we note R^i the set of reservoirs in subsystem i, and $R^{i,up}$ the set of reservoirs of R^i for which at least one upstream river section is in BS. C^i and S^i are the sets of hydro plants and river sections for which the upstream reservoir is in R^i.

L^i and Z^i represent the sets of electrical links and zones in subsystem i. $\mu_{r,t}$ (respectively $\lambda_{z,t}$, ν_t) is the estimated dual value of Eq. (4.2) (respectively Eq. (4.10), Eq. (4.11)). We also define r_s^{dn} as the reservoir downstream of river section s.

The MILP formulation for subsystem i is the following:

$$\begin{aligned}
\max \ & \sum_{r\in R^i} \omega_r.\mathbf{v}_{r,T} + \sum_{s\in S^i} \omega_{r_s^{dn}}.\mathbf{f}_{s,T} \\
& - \sum_{c\in C^i}\sum_{t=1}^{T} \theta.|\mathbf{q}_{c,t} - \mathbf{q}_{c,t-1}| + \sum_{r\in R^{i,up}}\sum_{t=1}^{T} \mu_{r,t}.(\mathbf{v}_{r,t} \\
& - \ \mathbf{v}_{r,t-1} - \sum_{s\in S_r^{up}\setminus BS} \zeta.\mathbf{o}_{s,t} + \sum_{s\in S_r^{dn}} \zeta.\mathbf{u}_{s,t}) \\
& + \ \sum_{z\in BZ}\sum_{t=1}^{T} \lambda_{z,t}.(\sum_{c\in E_z\cap C^i} \mathbf{p}_{c,t} \\
& + \ \sum_{l\in L_z^{in}\cap L^i} (\mathbf{b}_{l,t} - \Xi_l(\mathbf{b}_{l,t})) - \sum_{l\in L_z^{out}\cap L^i} \mathbf{b}_{l,t}) \\
& + \ \sum_{t=1}^{T} \nu_t.(\sum_{c\in C^i}\sum_{k\in K_{c,t}} \gamma_k.\mathbf{x}_{k,c,t})
\end{aligned} \tag{4.14}$$

subject to:

$$\mathbf{v}_{r,t} = \mathbf{v}_{r,t-1} + \zeta.\eta_{r,t} + \sum_{s\in S_r^{up}} \zeta.\mathbf{o}_{s,t} - \sum_{s\in S_r^{dn}} \zeta.\mathbf{u}_{s,t} \qquad \forall r \in R^i \setminus R^{i,up}, \forall t \tag{4.15}$$

$$\mathbf{u}_{s,t} = \sum_{c\in C_s} \mathbf{q}_{c,t} + \sum_{d\in D_s} \mathbf{w}_{d,t} \qquad \forall s \in S^i, \forall t \tag{4.16}$$

$$\mathbf{o}_{s,t} = \sum_{t'=0}^{\tau_s} \alpha_{s,t'}.\mathbf{u}_{s,t-t'} \qquad \forall s \in S^i, \forall t \tag{4.17}$$

$$\mathbf{f}_{s,t} = \mathbf{f}_{s,t-1} + \zeta.\mathbf{u}_{s,t} - \zeta.\mathbf{o}_{s,t} \qquad \forall s \in S^i, \forall t \tag{4.18}$$

$$\mathbf{h}_{c,t} = \Phi_{r_c}(\mathbf{v}_{r_c,t}) - \Psi_{s_c}(\mathbf{f}_{s_c,t}, \mathbf{u}_{s_c,t}) \qquad \forall c \in C^i, \forall t \tag{4.19}$$

$$\sum_{k\in K_{c,t}} \mathbf{x}_{k,c,t} = 1 \qquad \forall c \in C^i, \forall t \tag{4.20}$$

$$\mathbf{p}_{c,t} = \sum_{k\in K_{c,t}} \mathbf{g}_{k,c,t} \qquad \forall c \in C^i, \forall t \tag{4.21}$$

$$\mathbf{g}_{k,c,t} = \Pi_k(\mathbf{x}_{k,c,t}, \mathbf{q}_{c,t}, \mathbf{h}_{c,t}) \qquad \forall c \in C^i, \forall t, \forall k \in K_{c,t} \tag{4.22}$$

$$\delta_{z,t} = \sum_{c\in E_z} \mathbf{p}_{c,t} + \sum_{l\in L_z^{in}} (\mathbf{b}_{l,t} - \Xi_l(\mathbf{b}_{l,t})) - \sum_{l\in L_z^{out}} \mathbf{b}_{l,t} \qquad \forall z \in Z^i \setminus BZ, \forall t \tag{4.23}$$

$$\mathbf{x}_{k,c,t} \in \{0,1\} \qquad \forall c \in C^i, \forall t, \forall k \in K_{c,t} \tag{4.24}$$

To keep good calculation times, the subproblems must be solved separately: solving each subproblem generally takes less than 1 minute with a commercial solver, whereas finding a feasible solution to the combination of the subproblems takes around 40 minutes. The subproblems can even be tackled in parallel.

The combined solutions to the subproblems correspond to an integer solution of our original problem. It is locally optimal, but only partly feasible because the linking constraints may not be satisfied.

Solution repair

Finally, the method looks for a feasible integer solution to the original problem that is close to the intermediate solution given by the subproblems. To do so, the configuration choices are fixed as in the intermediate solution and the production is dispatched between the hydro plants to satisfy the constraints with the optimal efficiency.

That problem is linear and can be solved quickly, again on a well-tuned solver. If the fixed configurations prevent the satisfaction of the linking constraints during some periods, we may allow one more or less committed unit at each plant (then the problem becomes a small MILP, slightly longer to solve).

4.4 Computational Results

We tested our method on 9 real instances from HQP. The hydraulic network contains 8 hydro valleys, with 28 controllable hydro plants and 156 generating units. The electrical network is a connected graph with 26 electrical zones.

The water level functions are composed of 1 to 4 segments, depending on the characteristics of the reservoirs. For each hydro plant, each time step, and each configuration with at least one committed unit, the production function is represented by 9 extreme points: the configuration choice is binary, the turbined outflow has 4 discretization values and the dependance on the water head is supposed linear. For the configuration with no committed unit, the production function has only one point, corresponding to no turbined outflow and no production.

For each reservoir r, the final value of water ω_r is given by the dual value of the corresponding water conservation constraint in the medium-term model. Since the objective of the medium-term model is to maximize the efficiency of production, the water values decrease heading downstream.

The penalty term for the variations of turbined flow θ is defined as a small fraction of the maximum variation of final water value through the hydro plants, multiplied by a factor of

Table 4.1 Characteristics of the Instances

Instance	Season	Horizon (h)	Nb variables	Nb binaries	Nb constraints
1	Summer	72	186 703	11 942	112 035
2	Summer	168	437 134	27 981	261 795
3	Summer	240	626 053	40 132	374 314
4	Autumn	72	187 207	11 998	110 685
5	Autumn	168	440 725	28 380	258 875
6	Autumn	240	632 668	40 867	370 214
7	Winter	72	198 457	13 248	111 113
8	Winter	168	463 513	30 912	259 529
9	Winter	240	662 305	44 160	370 841

conversion for homogeneity:

$$\theta = 0.01 \cdot \zeta \cdot \max_{c \in C}(\omega_{r_c} - \omega_{n_c}) \tag{4.25}$$

where ω_{n_c} is the final water value of the reservoir downstream of hydro plant c. The penalty term must be very small compared to the rest of the objective, because avoiding the premature aging of the turbines is considered as a secondary objective at HQP. In our test cases, the penalized variations of turbined flow represent less than 0.1% of the objective.

The characteristics of the instances are given in Table 4.1. We chose 3 different lengths of horizon (3 days, 7 days, 10 days) and 3 different seasons (summer, autumn, winter). Indeed the length of horizon directly influences the size of the problem, but the season also impacts the complexity of the solution through the quantities of electrical load and natural inflows.

We partitioned the production system into 5 subsystems of variable size, as presented in Fig. 4.4. Subsystem S_1 contains 4 small hydro valleys, whereas subsystems S_4 and S_5 represent two branches of the same long hydro valley. The borders consist of three adjacent electrical zones and one river section.

Numerical tests were performed on a personal computer with an Intel Core Processor i5-4570, 4 cores at 3.20 GHz and 8.00 GB of RAM. CPLEX 12.6.2 (CPLEX, 2015) was used to solve the LPs and the MILPs. A threshold of 0.3% on the relative gap as been defined for the solutions of the subsystems. In practice, the first incumbent almost always satisfies this threshold.

Contrary to the heuristic currently used at Hydro-Québec, our method is able to produce a solution satisfying all the bounds, but also exploiting the available volumes in the reservoirs.

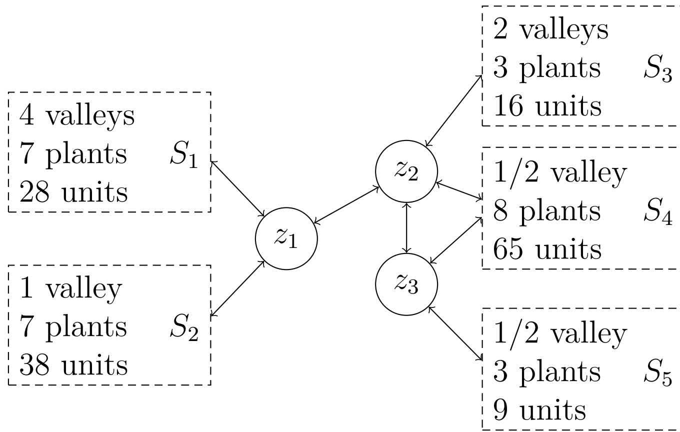

Figure 4.4 Schema of HQ's system decomposition.

No further comparison of the two methods has been shown relevant, due to great differences concerning the model and the characteristics of the production system.

Table 4.2 presents the solution times of the different phases and a bound on the final relative gap. Phases 1a and 1b correspond to the two LP solutions to estimate the marginal costs. During phase 2 the subsystems are solved independently; since they can be handled in parallel, only the time of the longest subsystem is recorded. Phase 3 is the repair of the integer solution. The bound on the final gap is given by the difference of objective functions between phase 1a and phase 3.

The final gaps are more than acceptable, and solving a 10 day-scenario takes less than 2.5 minutes. That makes our 3-phase method very well-suited for operational purpose. Yet, execution time seems to grow quadratically with the horizon size, which may not be much more extended without further decomposition (stage-wise).

We compared our method with a benchmark of generic MILP solvers: CPLEX 12.6.2 (CPLEX, 2015), Gurobi 6.5 (Gurobi, 2015) and SAS/OR 14.1 (SAS, 2015). For our particular problem and with the best tunings that we found on each solver, CPLEX has been the most efficient. Hence only the results of the latter are recorded.

Table 4.3 compares our 3 phase-method solution to the first solution obtained by CPLEX, in terms of objective function and execution time. In all cases, the solutions are extremely similar regarding the objective function: at most 3 GWh of variation. However, the 3 phase-method always saves more than 93% of the time needed by CPLEX.

Fig. 4.5 shows the correspondence between total power generation and total load in the aggregated solution of subsystems in case 3. While the electrical network is disconnected, the total generation is very close to the load, inferring that the marginal costs obtained at

Table 4.2 Solution Times of Different Phases (in Seconds)

Case	Phase 1a	Phase 1b	Phase 2	Phase 3	**Total**	Rel. gap
1	4.5	3.8	2.2	2.0	**12.5**	$\leq 0.01\%$
2	23.2	22.7	12.0	24.5	**82.5**	$\leq 0.02\%$
3	44.7	51.7	24.2	21.6	**142.2**	$\leq 0.03\%$
4	6.7	3.0	4.0	1.7	**15.4**	$\leq 0.01\%$
5	49.2	13.0	34.0	8.7	**104.8**	$\leq 0.01\%$
6	31.0	31.2	62.7	20.9	**145.9**	$\leq 0.02\%$
7	3.9	5.5	2.1	2.5	**14.0**	$\leq 0.01\%$
8	15.0	19.9	12.5	36.2	**83.6**	$\leq 0.01\%$
9	27.8	33.0	33.3	30.7	**124.7**	$\leq 0.01\%$

Table 4.3 Comparison Analysis with Heavy-Tuned Generic Solvers

	Objective function (GWh)			Execution time (s)		
Case	MILP	3 phases	**Diff**	MILP	3 phases	**Rel. diff**
1	84 425	84 426	**1**	401	12	**-97 %**
2	86 062	86 061	**-1**	6 380	82	**-99 %**
3	87 255	87 254	**-1**	14 687	142	**-99 %**
4	129 857	129 856	**-1**	846	15	**-98 %**
5	130 166	130 163	**-3**	5 514	105	**-98 %**
6	130 374	130 371	**-3**	16 149	146	**-99 %**
7	111 697	111 697	**0**	234	14	**-94 %**
8	109 078	109 078	**0**	1 143	84	**-93 %**
9	107 134	107 135	**1**	5 291	125	**-98 %**

the end of phase 1 are accurate enough.

Fig. 4.6 confronts the average marginal cost of the load constraint in the final solution to the ones in the continuous solutions in phase 1. As explained earlier, the marginal costs of phase 1b are higher than those of phase 1a, due to the greater accuracy in the production functions (and then less overestimation). In the final solution (phase 3), the sawtooth form of the average marginal cost is due to the discrete nature of the configuration choices. But the final solution still follows very closely the values of the continuous solutions.

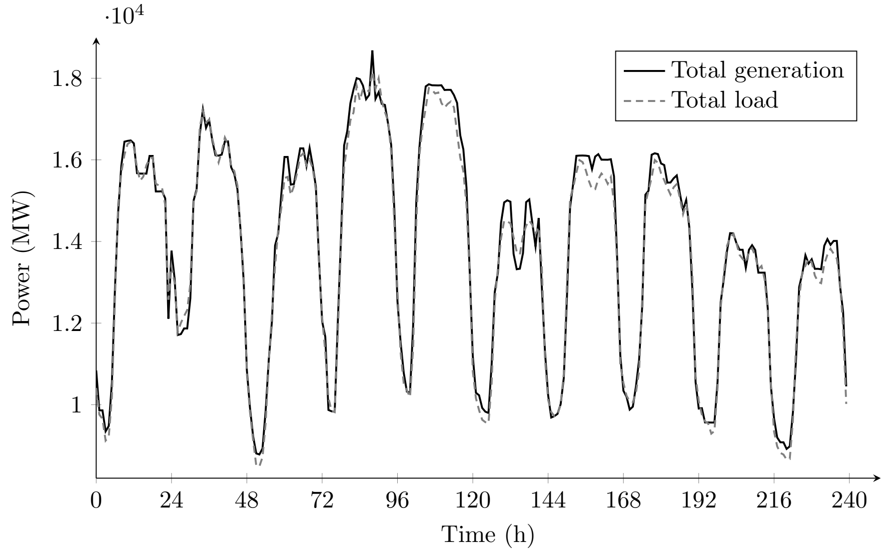

Figure 4.5 Case 3 comparison between total generated power and total load in phase 2.

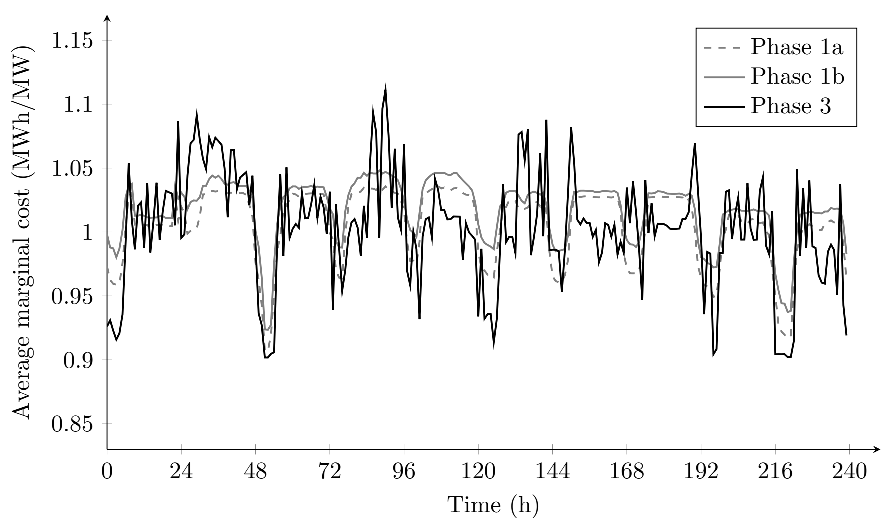

Figure 4.6 Case 3 average marginal cost of load constraint in different phases.

4.5 Conclusion

To solve the short-term hydro-generation planning problem on large-scale or complex systems, we have proposed a MILP model and a 3 phase-method to obtain near-optimal solutions very quickly. The method takes advantage of the special structure of the problem: few linking constraints between hydro valleys, and a very small integrality gap. We decompose the production system into local subsystems, and we estimate the marginal values of the global constraints in the convexified problem. Then we solve a local planning problem on each subsystem individually. Finally, we slightly modify the aggregated solution of the subsystems to find a near-optimal solution to the global planning problem. It must be emphasized that the effectiveness of our method is partly due to the small integrality gaps observed in our instances; should one face a situation where a large integrality gap is to be expected, other solution methods might be more appropriate. Our approach is flexible, since the MILP model can be easily adapted and the method is not dependent on the system partition. It also proved to be very fast and accurate on large-scale real-world instances. The good performance of our method makes it promising for future extensions of the model with stochastic inflows.

Acknowledgment

This research was supported by the NSERC/Hydro-Québec Industrial Research Chair on the Stochastic Optimization of Electricity Generation and Hydro-Québec Production. We also wish to thank the four anonymous referees who reviewed this paper for their valuable comments.

CHAPITRE 5 ARTICLE 2: AN EFFICIENT TABU SEARCH PROCEDURE FOR SHORT-TERM PLANNING OF LARGE-SCALE HYDROPOWER SYSTEMS

Alexia Marchand[1], Michel Gendreau[2], Marko Blais[3] et Grégory Emiel[4]

[1]Ph.D. candidate, Polytechnique Montréal, Montréal, Québec, Canada.

[2]Professor, Polytechnique Montréal, Montréal, Québec, Canada.

[3]Engineer, Hydro-Québec Production, Montréal, Québec, Canada.

[4]Optimization analyst, Hydro-Québec Production, Montréal, Québec, Canada.

Cet article a été soumis à la revue *Journal of Water Resources Planning and Management* le 29 mars 2018 et une révision a été soumise le 20 juin 2018. L'article est encore en processus de révision.

Abstract Short-term hydro-generation scheduling aims at minimizing water consumption for the next 7 to 15 days on an hourly basis, while satisfying the electrical load as well as many operational, regulatory and safety requirements. In an ever-changing environment, planners need to make decisions quickly and often adapt their schedules to new conditions. They need a tool that is fast, reactive, and flexible. This paper presents a new solution approach that provides, within a few minutes of computation, near-optimal solutions to hard problems, in which one seeks to determine the number of committed generating units, turbined and spilled flows on an hourly basis for a planning horizon of ten days. Our solution approach is based on tabu search with new neighborhoods, allowing simultaneous modifications for several plants and time periods. It can handle multi-objective problems, as well as non-linear and non-convex constraints. A decomposition mechanism allows parallelism and search acceleration for long horizons and large production systems. Computational experiments on real instances from Hydro-Québec show that even with the most naïve initial solution, our approach finds solutions almost as good as MILP solutions up to 235 times faster than conventional solvers and with fewer modeling limitations. Starting from a previous planning solution yields even better results.

5.1 Introduction

Hydropower planning aims at managing the hydro plants and spillways of a production system to minimize the consumption of potential energy stored in the reservoirs, while satisfying the electrical load and many operational constraints. Planners consider different horizons depending on the decisions to be made. Global volume trajectories and reservoir water values are determined in medium-term schedules, which are calculated for the next year in weekly time steps. These values are important inputs for short-term plans that are derived for a 7- to 15-day horizon on an hourly basis. The decisions to be made at each hour for the next days are the number of committed generating units and the turbined flow in each hydro plant, the spilled flow in each spillway, and the power transmitted through each link of the electrical network. Constraints concern equipment safety, flood control, outages, maintenance, grid operations, electrical reliability, regulations, environmental and recreational purposes. These constraints are requests from different stakeholders with different objectives. Sometimes, these objectives are contradictory (e.g., when a maintenance outage is requested on a generating unit during a period with high electrical demand).

Planners produce short-term schedules in two different contexts: one is operational, the other is analytical. Every day, an updated operational planning must be provided to the intra-day planners. On the other hand, ad-hoc impact analyses often have to be performed. For instance, planners may evaluate the outage cost of a given generating unit or electrical link during a given period, or compare different scenarios of demand and inflows. It should be noted that different models and solution methods will be more appropriate in each of the contexts. This article will focus on operational short-term planning for large power authorities relying on hydropower generation.

Short-term hydropower operational scheduling is subject to variability in the data: water inflows in the reservoirs, electrical load, run-of-river and wind generation, and equipment failures. While this variability could be accounted for through stochastic models, it is more usual in practice to adjust schedules on the basis of the most up-to-date information, sometimes several times per day. Hence, planners need a planning tool that quickly provides feasible operational schedules and that keeps operational flexibility in the production system. Operational flexibility is the key to quick and economic recourse, as explained in Karimanzira *et al.* (2016).

There are many articles dealing with the short-term generation planning problem, also called unit commitment problem: literature reviews by Tahanan *et al.* (2015), Taktak et D'Ambrosio (2017), and Osorio *et al.* (2013) record and categorize the most influential ones. However, only a tiny proportion of these articles deal with real-life problems for medium to large-scale production systems.

Several mathematical programming approaches have been applied to short-term hydropower planning. These include linear programming coupled to the successive linear programming heuristic Shawwash *et al.* (2000), mixed integer linear programming (MILP) Ge *et al.* (2014), and mixed integer non-linear programming (MINLP) Finardi et da Silva (2006); Catalão *et al.* (2010). While some of these approaches have rather successfully tackled real-life problems, it is important to highlight that linear programming is too restrictive in terms of mathematical modeling (e.g., it does not capture the discrete nature of some decisions, as well as some non-linear phenomena), and MILP and MINLP solvers are still unable to provide good schedules for large systems in an operational framework.

Dubost *et al.* (2005) and Marchand *et al.* (2018b) rely on decomposition and heuristics to handle very large-scale production systems, with relatively simple models. However, they cannot handle complex operating rules that would undermine the decomposition scheme upon which these methods rely. An important example of such rules is automatic generation control, which requires a subset of generating units to have the same production rate in order to ensure transmission network stability.

Moreover, short-term planners must often deal with contradictory requests from different stakeholders, which may lead to infeasible problems. Finding a physically coherent solution that is a good compromise between these requests then becomes a hard task. In a formal mathematical programming setting, this would imply either a very long constraint relaxation phase, or a huge number of additional variables and penalties, which would lead to unacceptable solution times.

Over the last thirty years, metaheuristics have become a competitive alternative to mathematical programming approaches to tackle complex combinatorial optimization problems. Some of the best-known methods include tabu search Glover (1989), genetic algorithms Holland (1973), simulated annealing Kirkpatrick *et al.* (1983), ant colony optimization Dorigo *et al.* (2006), and particle swarm optimization **?**. A comprehensive exposition to the field of metaheuristics can be found in Gendreau et Potvin (2010b). Several heuristics and metaheuristics approaches have been developed to solve the short-term hydropower planning problem Saravanan *et al.* (2013a). Senjyu *et al.* (2003) proposed a solution method based on priority lists; Mantawy *et al.* (1998) and Borghetti *et al.* (2001) implemented tabu search; Mahor et Rangnekar (2012) developed particle swarm optimization method and Hidalgo *et al.* (2015) proposed an approach based on genetic algorithms. Metaheuristics allow much more liberty than mathematical programming approaches in the mathematical representation of the problem. However, as far as the authors know, these methods have never reached operational solution times on large-scale problems with thousands of binary variables, because of their very slow exploration of the solution space.

This article proposes an operational solution tool for short-term scheduling of large-scale production systems, based on multi-neighborhood tabu search. The optimization model handles detailed physical representations of hydropower generation and the form of mathematical expressions is not restricted. Constraints and objectives are explicitly defined; hence, solutions and convergence can be evaluated and compared. The solution method is an efficient variant of the classical tabu search approach, thanks to several innovative features introduced in this paper: very large moves based on the simultaneous modification of several related decision variables, fast selection of the most promising moves, decomposition and parallelism. One could have considered other metaheuristics to tackle the short-term planning of hydropower systems. However, we chose to resort to tabu search because it is simple and well-documented, some of the authors had extensive previous experience with the method, and it turned out to be effective.

To the best of the authors' knowledge, this is the first time a metaheuristic approach is successfully applied to such a large and detailed short-term hydropower planning problem. This scheduling tool is highly modular: adding, removing and modifying constraints or objectives can be done at very low computational cost. Hence it easily follows the ever-changing operational context. It can always provide a physically coherent schedule, thus allowing the decision-maker to adjust the solution time to his needs and constraints: if desired, a solution can be obtained quickly, but if time is available, improved solution can be computed. Finally, the decision-maker can use the mathematical representation as an exploration tool: he can impose decisions and evaluate any schedule on graphical and non-quantifiable criteria.

While our approach is general, our work was motivated by the planning problems at Hydro-Québec Production, the largest hydropower producer in North America. Its production system is composed of 12 hydro valleys with 63 hydro plants and 27 reservoirs, totalling 176 TWh of storage capacity Hydro-Québec (2017). Computational experiments are performed on real instances from Hydro-Québec.

5.2 System representation

5.2.1 System Constraints

Hydraulic network

The hydraulic network is composed of hydro valleys, with reservoirs, hydro plants, spillways, and river sections between the reservoirs. The hydraulic network considered in this article is represented in Fig. 5.1. It is composed of six main hydro valleys; the others are run of the river.

In our deterministic context, the dynamics of a hydro valley are entirely determined by the turbined flow in its plants and the spilled flow in its spillways throughout the horizon.

At each time step, the upcoming flow into a given river section is the total flow of the upstream hydro plants and spillways.

$$u_{s,t} = \sum_{c \in C_s^{up}} q_{c,t} + \sum_{d \in D_s^{up}} w_{d,t} \tag{5.1}$$

where $u_{s,t}$ = upcoming water flow into river section s at time step t (m^3/s); $q_{c,t}$ = turbined flow at hydro plant c during time step t (m^3/s); C_s^{up} = set of hydro plants directly upstream of river section s; $w_{d,t}$ = spilled flow at spillway d during time step t (m^3/s); and D_s^{up} = set of spillways directly upstream of river section s.

The outgoing flow from each river section depends on the past upcoming flows and the delays associated to the river section.

$$o_{s,t} = \sum_{t'=0}^{\tau_s} \alpha_{s,t'}^{prop}.u_{s,t-t'} \tag{5.2}$$

where $o_{s,t}$ = outgoing flow from river section s at time step t (m^3/s); τ_s = maximum number of time steps for water to transit in river section s; and $\alpha_{s,t'}^{prop}$ = proportion of upcoming water taking t' time steps to transit in river section s.

The volume of each reservoir is determined by the water flow in the upstream and downstream river sections.

$$v_{r,t} = v_{r,t-1} + \gamma_t^{conv}.(i_{r,t} + \sum_{s \in S_r^{up}} o_{s,t} - \sum_{s \in S_r^{dn}} u_{s,t}) \tag{5.3}$$

where $v_{r,t}$ = volume of reservoir r at the end of time step t (hm^3); $i_{r,t}$ = natural inflow at reservoir r during time step t (m^3/s); γ_t^{conv} = conversion factor for water flow to volume at time step t (hm^3/(m^3/s)); and S_r^{up}, S_r^{dn} = sets of river sections respectively directly upstream and directly downstream of reservoir r.

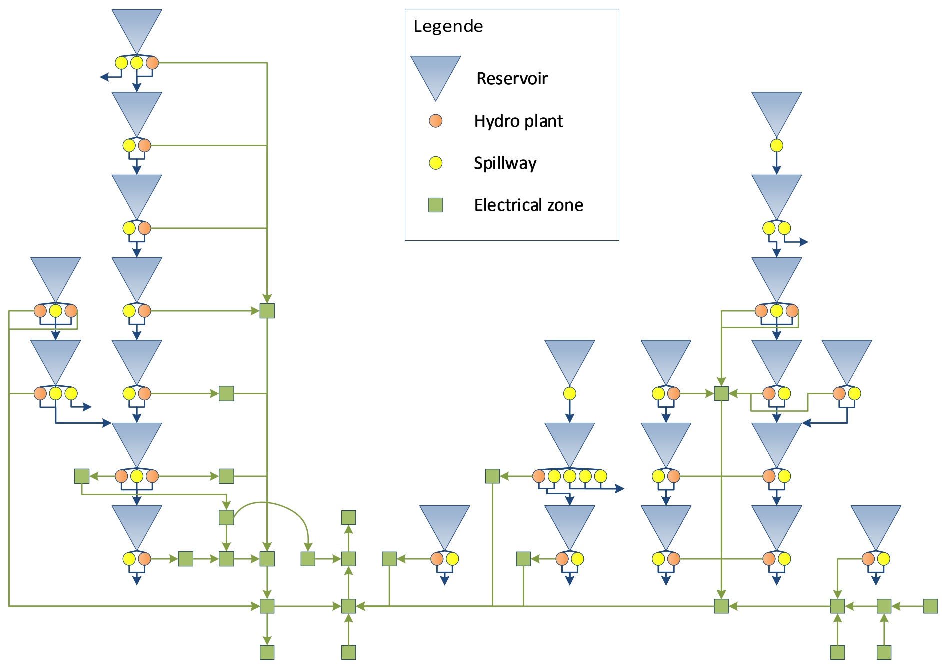

Figure 5.1 Hydro-Québec's production system diagram.

Power generation

The power generation of a hydro plant depends on whether each generating unit is working or not, as well as on the turbined flow and the net water head at each unit. Deciding the state of each generating unit leads to a very hard problem, called the unit commitment problem. This problem can be broken down into two steps. The first step consists in determining, for each hydro plant and each time step, for each possible number of committed units, the best combination of units (e.g., if two units are committed, this step determines which two it will be). It is important to note that the selection may vary along the horizon, to account for the availability of each unit. The second step consists in choosing, for each hydro plant and each time step, the number of committed units and the turbined flow in the plant. It should be pointed out that, because of the work performed in the first step, decisions on the commitment status of each generating unit are replaced by decisions on the number of committed units in each hydro plant. This is a good approximation because in practice, committed units are usually the most efficient, and generating units are very similar in each hydro plant. Furthermore, this problem separation considerably reduces the symmetry inherent in the unit commitment problem.

For short-term planning at Hydro-Québec, the first step of the unit commitment problem is already solved. Hence, for each hydro plant and time step, a given number of committed units is associated with a power generation function that depends only on the turbined flow and the water head.

The water head corresponds to the difference between the upstream reservoir level and the tail-race water level, which depends itself on the water volume in the downstream reservoir and the upcoming flow in the downstream river section.

$$h_{c,t} = f_c^{up}(v_{r_c^{up},t}) - f_c^{dn}(v_{r_c^{dn},t}, u_{s_c^{dn},t}) \tag{5.4}$$

where $h_{c,t}$ = water head of hydro plant c at the end of time step t (m); r_c^{up} = index of reservoir directly upstream of hydro plant c; $f_c^{up}(.)$ = upstream water level function of hydro plant c (m), and is a piecewise linear function of the upstream reservoir volume $v_{r_c^{up},t}$; s_c^{dn} = index of river section directly downstream of hydro plant c; and $f_c^{dn}(.)$ = tail-race water level function of hydro plant c (m), and is a linear function of the downstream reservoir volume and the total upcoming flow in the downstream river section.

The generated power at each hydro plant and time step depends on the number of committed units, the turbined flow and the water head. The generation function is intentionally kept generic here, since there is no restriction on its definition.

$$k_{c,t} \in \{0, 1, .., K_{c,t}\} \tag{5.5}$$

$$p_{c,t} = f_{c,t}^{gen}(k_{c,t}, q_{c,t}, h_{c,t-1}) \tag{5.6}$$

where $k_{c,t}$ = number of committed units in hydro plant c during time step t; $K_{c,t}$ = number of available units in hydro plant c during time step t; $p_{c,t}$ = generated power at hydro plant c during time step t (MW); $f_{c,t}^{gen}(.)$ = power generation function of hydro plant c during time step t, depending on the number of committed units $k_{c,t}$, the turbined flow $q_{c,t}$ and the water head $h_{c,t-1}$.

Fig. 5.2 represents a generation function and its evolution as the water head varies. Several curves are plotted, from the minimum water head (0 %) to the maximum (100 %).

Fig. 5.3 illustrates different generation functions at given hydro plant and time step, depending on the number of committed units. Because units can only operate for turbined flows in some interval, some ranges of flow or generated power might be infeasible (e.g., between the generation functions with 1 and 2 units). When several units are committed, there may be several ways to turbine some flows, which leads to an overlap of functions. Furthermore, the dashed line represents theoretical power generated with the best efficiency. It highlights the

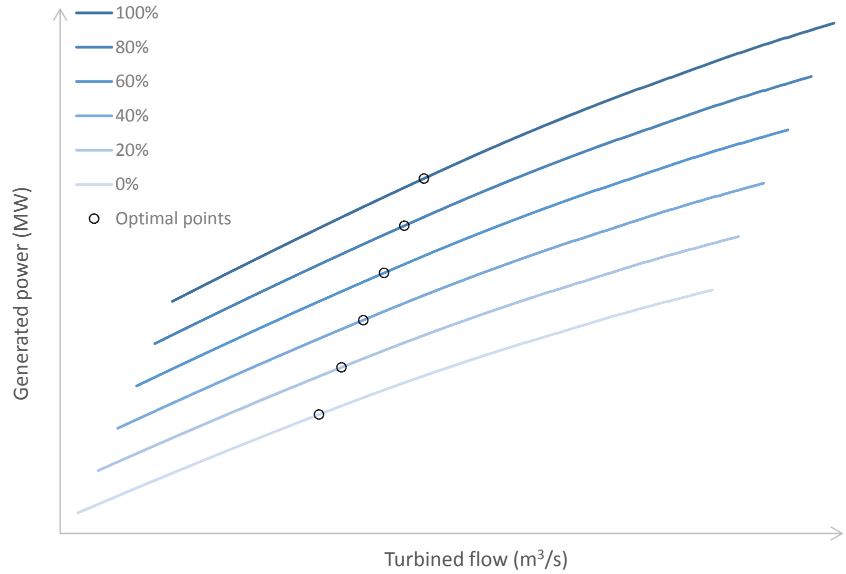

Figure 5.2 Power generation function depending on turbined flow and relative water head, for a given hydro plant and a given group configuration.

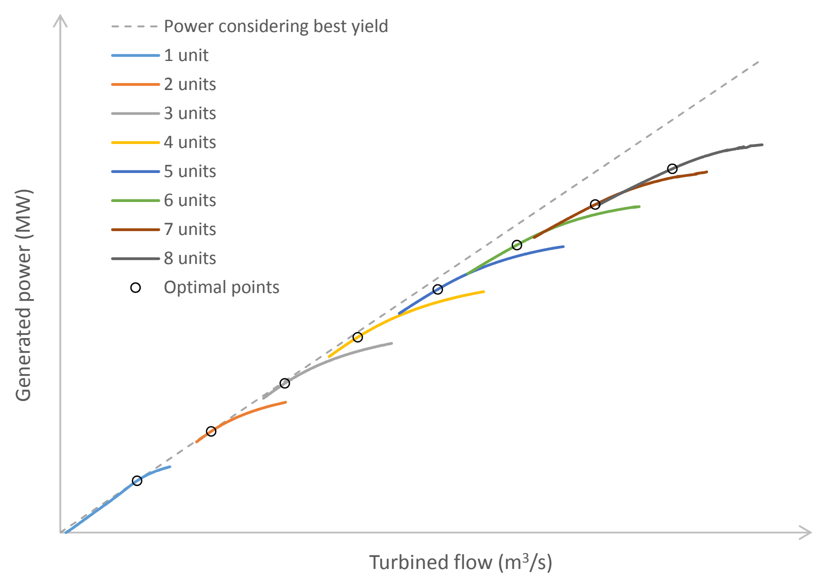

Figure 5.3 Example of available power generation functions at given hydro plant and time step.

loss in yield as the number of committed units grows. This is mainly due to the increasing elevation of the tailwater level for large turbined flows.

Electrical network

The electrical network is represented by a graph in which the nodes are called electrical zones and the edges electrical links. Each zone is associated with a (possibly empty) set of plants and a local load (positive or negative, depending on forecast exchanges, run-of-river and wind generation). Losses are taken into account in a very simple way due to the lack of information on their nature. A loss coefficient α_l^{loss}, computed from empirical data, is associated to each electrical link l.

To represent the power transmitted through the electrical links, each link is given an arbitrary direction. $b_{l,t}$ represents the power flow during time step t through link l, from its source zone to its destination zone. The transmitted power between a link and its source zone depends on the flow direction. Since the link directions are defined arbitrarily, the value of power transmitted between a link and its destination zone is the opposite.

$$f^{src}(b_{l,t}) = \begin{cases} b_{l,t} & \text{if } b_{l,t} \geq 0 \\ (1-\alpha_l^{loss})b_{l,t} & \text{otherwise} \end{cases} \tag{5.7}$$

$$f^{dest}(b_{l,t}) = \begin{cases} (1-\alpha_l^{loss})b_{l,t} & \text{if } b_{l,t} \geq 0 \\ b_{l,t} & \text{otherwise} \end{cases} \tag{5.8}$$

where $b_{l,t}$ = relative value of power transmitted through link l during time step t (MW); and $f^{src}(b_{l,t}), f^{dest}(b_{l,t})$ = relative value of power transmitted from link l to its source and destination zones, depending on the power transmitted through the link $b_{l,t}$ (MW).

At each electrical zone and each time step, the difference between production and load is obtained by energy conservation.

$$e_{z,t} = \sum_{c \in E_z} p_{c,t} + \sum_{l \in L_z^{in}} f^{dest}(b_{l,t}) + \sum_{l \in L_z^{out}} f^{src}(b_{l,t}) - \delta_{z,t} \tag{5.9}$$

where $e_{z,t}$ = difference between production and load at zone z during time step t (MW); E_z = set of hydro plants associated to zone z; L_z^{in}, L_z^{out} = set of electrical links upcoming to and outgoing from zone z; and $\delta_{z,t}$ = net load at zone z during time step t (MW).

Given a time step t and the generated power at each hydro plant, the values of transmitted power through each link and differences between production and load are calculated by solving a simple minimum-cost flow problem Ahuja *et al.* (1989). Eqs. 5.7 - 5.9 represent the constraints, and the objective is indeed the sum of the losses in the links $\sum_{l \in L} \alpha_l^{loss} b_{l,t}$. Each variable $b_{l,t}$ is bounded by the minimum and maximum capacity of link l during time step t. This well-known problem is easily solved by linear programming and by many network flow algorithms; a variant of the Ford-Fulkerson algorithm **?** is used in this paper.

The power transmission variables are the optimal solution of a minimum cost-flow problem at each time step. Hence, they are not decisions but adjustment variables.

The electrical network considered in this article is represented in Fig. 5.1. For each hydro plant in run-of-the-river valleys and each time step, power generation is precalculated and substracted from the load at the associated electrical zone.

5.2.2 Operational Constraints

Load following

Due to stability considerations in the electrical network, variations of the number of committed units must be in the same direction as variations of the total load. This is valid for each hydro plant and each time step:

$$k_{c,t} \begin{cases} \geq k_{c,t-1} & \text{if } \sum_{z \in Z} \delta_{z,t} \geq \sum_{z \in Z} \delta_{z,t-1} \\ \leq k_{c,t-1} & \text{otherwise} \end{cases} \tag{5.10}$$

Therefore, the domain of the decision variables may be reduced at each time step, depending on the decisions taken at the preceding time step.

Automatic generation control

The production system is submitted to automatic generation control (AGC), in order to quickly respond to load fluctuations. At each time step, a set of hydro plants is flagged as part of the AGC. These hydro plants all have the same production rate, and within the limits of their generation functions, they produce exactly the difference between the total load and the production of the other plants.

For the sake of clarity, the set of hydro plants taking part to the AGC is assumed to be the same at each time step and is denoted by C^{AGC}. The complementary set of hydro plants is $C^{stb} = C \backslash C^{AGC}$.

The production rate of the plants in C^{AGC} is defined as the bounded ratio between the load not satisfied by the other plants, and their capacity range. This production rate determines the production of each hydro plant. The turbined flow is then deduced, using the inverse generation function, and considering the number of committed units and the water head. Therefore, the turbined flows of the plants in C^{AGC} are not decision variables.

$$d_t^{AGC} = \sum_{z \in Z} \delta_{z,t} - \sum_{c \in C^{stb}} p_{c,t} \tag{5.11}$$

$$y_t^{AGC} = \begin{cases} 0 & \text{if } d_t^{AGC} \leq \sum_{c \in C^{AGC}} p_{c,t}^{min} \\ 1 & \text{if } d_t^{AGC} \geq \sum_{c \in C^{AGC}} p_{c,t}^{max} \\ \frac{d_t^{AGC} - \sum_{c \in C^{AGC}} p_{c,t}^{min}}{\sum_{c \in C^{AGC}} (p_{c,t}^{max} - p_{c,t}^{min})} & \text{otherwise} \end{cases} \qquad \forall t \tag{5.12}$$

$$p_{c,t} = (1 - y_t^{AGC}).p_{c,t}^{min} + y_t^{AGC}.p_{c,t}^{max} \qquad \forall c \in C^{AGC}, \forall t \tag{5.13}$$

$$q_{c,t} = \left(f_{c,t}^{gen}\right)^{-1}(k_{c,t}, p_{c,t}, h_{c,t-1}) \qquad \forall c \in C^{AGC} \tag{5.14}$$

where $p_{c,t}^{min}, p_{c,t}^{max}$ = minimum and maximum capacity of hydro plant c during time step t, depending on $k_{c,t}$ and $h_{c,t}$ (MW); d_t^{AGC}, y_t^{AGC} = demand and production rate of the AGC hydro plants during time step t; and $\left(f_{c,t}^{gen}\right)^{-1}(.)$ = inverse generation function of hydro plant c during time step t, giving the turbined flow $q_{c,t}$ depending on the number of committed units $k_{c,t}$, the generated power $p_{c,t}$, and the water head $h_{c,t-1}$.

5.3 Quality measurement of an operational schedule

The aim of short-term scheduling is to keep the production system as efficient as possible, while satisfying operational constraints and following the volume trajectories given by the medium-term planning. Since operational constraints come from different stakeholders with different objectives, they may be contradictory. To ensure the problem feasibility, constraints are modeled as penalties to be minimized. The feasibility criteria are the most important for short-term scheduling. System efficiency plays a minor part.

5.3.1 Satisfaction of Bounds

The hydro planners need to respect operational constraints as much as possible. These constraints may concern the number of committed units or the turbined flow in each plant (e.g., for maintenance on the turbines or the electrical network), or the spilled flow in each spillway (e.g., for ecological reasons).

We introduce three feasibility scores that correspond to the sum of squared bound violations concerning the number of committed units, the turbined flow and the spilled flow.

$$obj^k = \sum_{t=1}^{T} \sum_{c \in C} (\max(k_{c,t} - k_{c,t}^{max}, k_{c,t}^{min} - k_{c,t}, 0))^2 \tag{5.15}$$

$$obj^q = \sum_{t=1}^{T} \sum_{c \in C} (\max(q_{c,t} - q_{c,t}^{max}, q_{c,t}^{min} - q_{c,t}, 0))^2 \tag{5.16}$$

$$obj^w = \sum_{t=1}^{T} \sum_{d \in D} (\max(w_{d,t} - w_{d,t}^{max}, w_{d,t}^{min} - w_{d,t}, 0))^2 \tag{5.17}$$

where obj^k, obj^q, obj^w = objective terms for the satisfaction of the bounds corresponding to the number of committed units, the turbined flow ($(\text{m}^3/\text{s})^2$) and the spilled flow ($(\text{m}^3/\text{s})^2$); $k_{c,t}^{min}, q_{c,t}^{min}, w_{d,t}^{min}$ = minimum bounds of $k_{c,t}$, $q_{c,t}$ (m^3/s) and $w_{d,t}$ (m^3/s); and $k_{c,t}^{max}, q_{c,t}^{max}, w_{d,t}^{max}$ = maximum bounds of $k_{c,t}$, $q_{c,t}$ (m^3/s) and $w_{d,t}$ (m^3/s).

They also need to keep the reservoir volumes close to the ones in the medium-term planning. Then each reservoir has minimum and maximum volume bounds at each time step, representing small deviations from the volume in the medium-term planning. Hence the objective relative to the satisfaction of bounds is defined as follows.

$$obj^v = \sum_{t=1}^{T} \sum_{r \in R} (\max(v_{r,t} - v_{r,t}^{max}, v_{r,t}^{min} - v_{r,t}, 0))^2 \tag{5.18}$$

where obj^v = objective term corresponding to the satisfaction of the volume bounds ($(\text{hm}^3)^2$).

5.3.2 Satisfaction of Load

The load must be satisfied as much as possible. Usually, the total load is easily satisfied thanks to the AGC, but some local loads may not be satisfied because of the transmission constraints. The objective term corresponding to the satisfaction of load is defined as the sum of the squared differences between production and load at each electrical node.

$$obj^{load} = \sum_{t=1}^{T} \sum_{z \in Z} e_{z,t}^2 \tag{5.19}$$

where obj^{load} = objective term corresponding to the satisfaction of the load ($(\text{MW})^2$).

5.3.3 System Efficiency

The system efficiency of a schedule is evaluated with the final value of water stored in the reservoirs. The water values are given by the medium-term model, and correspond to a productivity signal for each reservoir. They are decreasing along the rivers.

$$f_{s,t} = f_{s,t-1} + \gamma_t^{conv}.(u_{s,t} - o_{s,t}) \tag{5.20}$$

$$x_t = \sum_{r \in R} \omega_r.(v_{r,t} + \sum_{s \in S_r^{up}} f_{s,t}) \tag{5.21}$$

where $f_{s,t}$ = volume in transit in river section s at the end of time step t (hm^3); x_t = global value of water at the end of time step t (MWh) ; and ω_r = water value of reservoir r (MWh/hm^3).

The objective term representing system efficiency is the value of water used during the horizon, i.e., the difference between the maximal and the actual global value of water at the end of the horizon. Since the water values are decreasing along the rivers, the maximal final value of water is the sum of the initial value of water and the inflows.

$$x_T^{max} = x_{-1} + \sum_{t=1}^{T} \sum_{r \in R} \omega_r.\gamma_t^{conv}.i_{r,t} \tag{5.22}$$

$$obj^{eff} = x_T^{max} - x_T \tag{5.23}$$

where x_T^{max} = maximal global value of water at the end of the horizon (MWh); x_{-1} = global value of water at the beginning of the horizon (MWh); and obj^{eff} = objective term corresponding to global efficiency (MWh).

5.3.4 Start-Ups and Shut-Downs

To avoid premature aging of generating units, start-ups and shut-downs must be minimized. Hence, the objective term obj^{ss} penalizes variations of the number of committed units in each plant:

$$obj^{ss} = \sum_{t=1}^{T} \sum_{c \in C} |k_{c,t} - k_{c,t-1}| \tag{5.24}$$

where $|.|$ is the absolute value function.

5.3.5 Global Objective

The global objective function of the problem is the weighted sum of the criteria cited above. The objective is to minimize it.

$$obj^{glob} = \lambda^k.obj^k + \lambda^q.obj^q + \lambda^w.obj^w + \lambda^v.obj^v + \lambda^{load}.obj^{load} + \lambda^{eff}.obj^{eff} + \lambda^{ss}.obj^{ss} \tag{5.25}$$

where obj^{glob} = global objective value; and $\lambda^k, \lambda^q, \lambda^w, \lambda^v, \lambda^{load}, \lambda^{eff}, \lambda^{ss}$ = objective coefficients for the number of committed units, the turbined flow ($1/(\mathrm{m}^3/\mathrm{s})^2$), the spilled flow ($1/(\mathrm{m}^3/\mathrm{s})^2$), the reservoir volumes ($1/(\mathrm{hm}^3)^2$), the load satisfaction ($1/(\mathrm{MW})^2$), the final value of water (1/MWh), and the start-ups and shut-downs.

Objective coefficients balance the contribution of each term to the global objective. They are normalized by setting the value of λ^v to 1. Other objective coefficient values are calibrated via a trial and error process. Their order of magnitude range from 10^{-2} (for λ^{load}) to 10^2 (for λ^k), in order to take into account their different units.

5.4 Optimization problem and solution approach

In this context, finding the best operational schedule corresponds to minimizing the global objective obj^{glob} while satisfying the constraints in Eqs. (5.1)-(5.25). This problem is a mixed-integer nonlinear problem, due to the integer variables for the number of committed units and the nonlinear generation functions in the hydro plants.

With the definitions in the constraints, the decision variables at each time step t are :

- the number of committed units $k_{c,t}$ at each hydro plant $c \in C$;
- the turbined flow $q_{c,t}$ at each hydro plant $c \in C^{stb}$;
- and the spilled flow $w_{d,t}$ at each spillway $d \in D$.

The other variables (except the power transmission variables) can be calculated with Eqs. (5.1)-(5.25). Each time a decision variable is modified at a given time step t, it affects the generated power at the neighboring hydro plants during the rest of the horizon (because of a variation in water heads). Therefore, the power transmisson variables are updated for each time step $t' \geq t$ by solving the minimum-cost flow problem (as defined in the section describing the electrical network).

The general idea of our approach is to iteratively apply small changes (moves) to the decision variables until the global objective cannot be improved anymore. The operational schedule of the day before can be used as a starting solution. However, like in most combinatorial problems, direct implementation of local search usually leads to local optima of poor quality. To circumvent this difficulty, Glover (1986) proposed using additional information structures to give the algorithm the ability to get out of local optima. In particular, short-term memories (tabu lists) forbid the reversal of recent moves and thus prevent cycling when local search is pursued from local optima. Other memories can be used to reinforce attractive moves, or to redirect the search to more promising solutions. The resulting method is called tabu search Glover (1989, 1990). For a more recent overview of tabu search, see Gendreau et Potvin

(2010b). Tabu search is well documented and has already given good results to the unit commitment problem on small and medium-size production systems Borghetti *et al.* (2001).

5.5 Schedule adjustment with parallel tabu search

5.5.1 Moves

Elementary moves

Our problem is not entirely combinatorial, due to the decisions on the spilled flow in the spillways and on the turbined flow at the hydro plants in C^{stb}. However, these variables can be discretized.

Here, an elementary move is defined as a variation of decision variables at a given time step, and at a given hydro plant or spillway. These moves are different whether we consider a hydro plant or a spillway, and if a hydro plant, whether it participates in the AGC or not.

Considering move direction $dir \in \{up, dn\}$, elementary move $m^{k}_{dir,c,t}$ consists in committing ($dir = up$) or decommitting ($dir = dn$) a generating unit at hydro plant c during time step t. When a move is made, the turbined flow at the corresponding hydro plant and time step is adjusted in order to keep as much as possible the same production rate.

For each hydro plant in C^{stb}, the generation functions are discretized in several points, including at least the minimum, optimum, and maximum points. The elementary move $m^{q}_{dir,c,t}$ consists in modifying the turbined flow $q_{c,t}$ to the next discretization point, depending on move direction dir.

Spilled flows are also discretized, with discretization steps that can be different for each spillway and each time step. As for the turbined flows, $m^{w}_{dir,d,t}$ is the elementary move towards the closest discretization point from the current spilled flow $w_{d,t}$ in move direction dir.

After each move, the turbined flow is adjusted in the hydro plants in C^{AGC}, in order to satisfy the load as much as possible, and the transmitted power is recalculated in the electrical links.

Large moves

In order to follow the load and to reduce stress and fatigue, generating units are generally committed or uncommitted during several hours. This behavior is reproduced in the search by allowing *large moves* during time periods longer than one time step.

In Hydro-Québec production system, head reservoirs are usually very large, while the others do not have enough capacity to absorb large inflow variations during long periods. Therefore, reservoirs release flow must be partly synchronized along each river. For this reason, it should be more efficient to allow moves for sequences of plants.

Large hydro plants moves are defined with a sequence of hydro plants (instead of one plant), a time interval (instead of one time step) and a direction.

Each hydro plant is given a time constant corresponding to the number of time steps it can adjust its number of committed units without implying the upstream or downstream hydro plants. $C^m_{c,s}$ is the set of hydro plants that should adjust with hydro plant c during a time interval of size s in order to satisfy the volume bounds on the reservoirs. The large move $m^{lrg,k}_{dir,c,i}$ consists in applying all the moves $m^k_{dir,c',t}$ for each hydro plant $c' \in C^m_{c,|i|}$ and each time step t in interval i.

Variations of turbined and spilled flow must also be reduced to avoid damage to the equipment; hence, moves on long time intervals are also useful for these types of decision variables. The large move $m^{lrg,q}_{dir,c,i}$ (resp. $m^{lrg,w}_{dir,d,i}$) is defined as the combination of moves $m^q_{dir,c,t}$ (resp. $m^w_{dir,d,t}$) for each time step t in interval i.

5.5.2 Neighborhoods

Tabu search is performed on seven neighborhoods, which are based on elementary or large moves. The different neighborhoods are defined in the following paragraphs.

Neighborhoods with elementary moves

The notation $M^{elm,k}$ represents the neighborhood composed of all the solutions obtained with any elementary move $m^k_{dir,c,t}$ and compatible with the load following constraints. Neighborhood $M^{elm,q}$ is the union of all the solutions obtained by any move $m^q_{dir,c,t}$ on any hydro plant $c \in C^{stb}$. Neighborhood $M^{elm,w}$ is the union of solutions obtained by any move $m^w_{dir,d,t}$.

Neighborhoods on maximal intervals

Moves have more impact on the objective value as their intervals are larger. However, they will not improve the solution if they do not respect the bounds or follow the load. Hence, we define neighborhoods $M^{\max,k}$, $M^{\max,q}$ and $M^{\max,w}$ as sets of moves on the maximal intervals that satisfy these constraints.

Neighborhood on intervals considering production and demand

I_{up} represents the set of the largest intervals during which total production is lower than total demand, with a given tolerance level $\Delta \geq 0$. Likewise, I_{dn} is the set of the largest intervals during which total production is greater than total demand, with tolerance level $\Delta \geq 0$.

$$I_{up} = \{[t_1, t_2] \mid P_t \leq D_t + \Delta \, \forall t \in [t_1, t_2], P_{t_1-1} > D_{t_1-1} + \Delta, P_{t_2+1} > D_{t_2+1} + \Delta\} \quad (5.26)$$

$$I_{dn} = \{[t_1, t_2] \mid P_t \geq D_t - \Delta \, \forall t \in [t_1, t_2], P_{t_1-1} < D_{t_1-1} - \Delta, P_{t_2+1} < D_{t_2+1} - \Delta\} \quad (5.27)$$

where P_t, D_t = total production and total demand during time step t (MW).

Fig. 5.4 illustrates the sets of largest intervals I_{up} and I_{dn} for a given solution on a 24-hour horizon. With tolerance level Δ, intervals of I_{up} and I_{dn} may overlap when $|P_t - D_t| \leq \Delta$. Furthermore, the presence of Δ allows for larger intervals I_{up} and I_{dn}, which in turn bring more possible moves (see below).

For each direction move dir, hydro plant c and interval $i \in I_{dir}$, $I^m_{dir,c,i}$ corresponds to the set of the $n.|i|$ largest intervals i' for which the move $m^{lrg,k}_{dir,c,i'}$ is possible (depending on the available units and the load following constraints). n is a user-defined parameter controlling the size of the large neighborhood.

The demand neighborhood $M^{dem,k}$ is the union of the large moves defined on all the intervals $I^m_{dir,c,i}$.

$$M^{dem,k} = \{m^{lrg,k}_{dir,c,i'} \mid \forall dir, \forall c, \forall i \in I_{dir}, \forall i' \in I^m_{dir,c,i}\} \quad (5.28)$$

It is important to highlight the novelty of this demand neighborhood. While in most applications of tabu search, or other local-search based metaheuristics, neighborhoods are defined on the basis of changes performed on a single or a small number of decision variables, we consider here the simultaneous modification of several related variables: in fact, variables defined for an interval of several time periods for several plants.

5.5.3 Tabu Search

Tabu list

Moves involving at least one of the hydro plants or the spillway modified in the last move and its opposite direction, are tabu during the next N^{tabu} iterations, where N^{tabu} is a user-defined parameter. The tabu list is the collection of these moves.

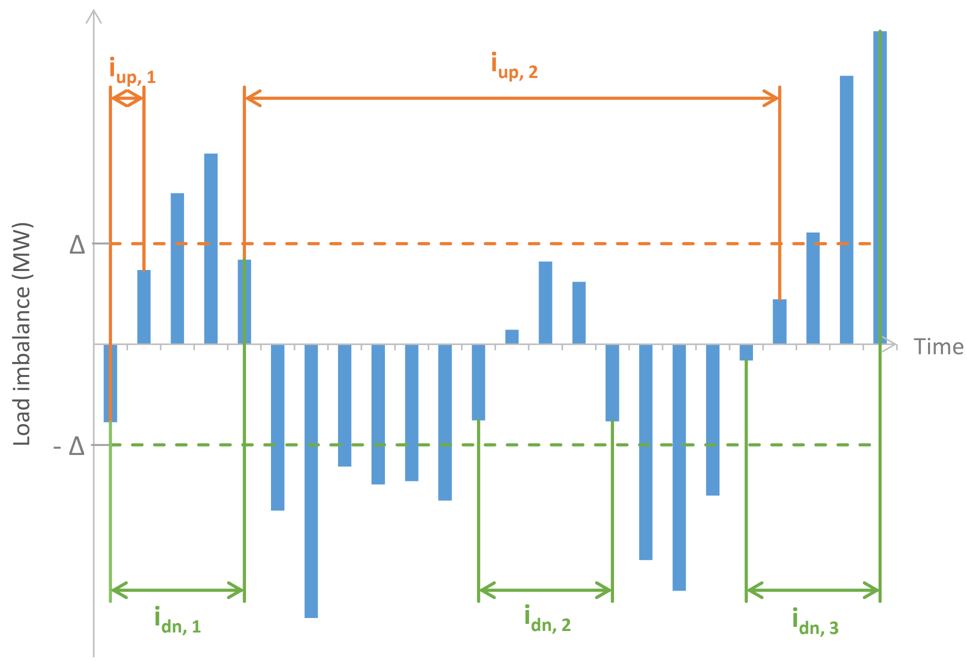

Figure 5.4 Sets of largest intervals $I_{up} = \{i_{up,1}, i_{up,2}\}$ and $I_{dn} = \{i_{dn,1}, i_{dn,2}, i_{dn,3}\}$.

Local search

The very large neighborhoods prevent us from testing all the possible neighbors at each iteration. We apply a first-improvement strategy for a given neighborhood, with an aspiration criterion.

To improve computational efficiency, the neighbors are sorted depending on their potential to improve the objectives, and tested in this order via an in-house simulation algorithm. The potentials to improve the objectives are based on approximations of the objectives concerning the bounds (obj^k, obj^q, obj^w, obj^v) and the satisfaction of load (obj^{load}), which appear to be the most significant.

The potential for improving the bounds is calculated as the sum of the penalties of the following bounds:

— the volume bounds violations of the upstream and downstream reservoirs during the time interval of the move and the next 72 hours;

— the bounds violations concerning the hydro plants or the spillway during the time interval of the move.

Different lengths of time have been tested to estimate the volume bounds violations. 72 hours after the end of the move gave the best results in terms of optimality and computation time.

The potential for improving the satisfaction of load is the sum of the penalties due to the difference between production and demand during the time interval of the move.

Global termination criteria

The algorithm is stopped whenever one of the two following criteria is met:

— there has been no improvement on the best found objective in the last N^{max} iterations,

— or the total number of iterations has reached N^{total};

where N^{max} and N^{total} are user-defined parameters.

Intensification

The demand neighborhood $M^{dem,k}$ turns out to be the most effective neighborhood. However, the other neighborhoods can also be useful during the search. Then each neighborhood is given termination criteria as defined in the previous paragraph, and when one of them is satisfied, the search continues with the next neighborhood, until one of the termination criteria of the global search are satisfied.

The neighborhoods are explored in the following order : $M^{dem,k}$, $M^{\max,k}$, $M^{\max,q}$, $M^{elm,k}$, $M^{elm,q}$, $M^{\max,w}$, $M^{elm,w}$. This order has been chosen to prioritize the neighborhoods where one could expect to find moves having the largest impact on the objective value. If the search on the last neighborhood $M^{elm,w}$ is terminated but the global termination criteria are not satisfied, then the search continues with the first neighborhood $M^{dem,k}$.

Diversification

To keep the algorithm from being trapped in a small region of the search space, continuous diversification is added to the algorithm Gendreau et Potvin (2010b). Moves are penalized in the calculation of their potential to improve the objectives, depending on the number of times the associated element (hydro plant or spillway) and direction have been rejected before.

Hence, whenever the algorithm rejects a move, this latter and similar moves (with same element and direction) will be more penalized. If the algorithm keeps testing them without success, they will eventually drop down in the list of moves to be tested.

5.5.4 Decomposition and parallelism

The search is accelerated by dividing it between several threads. The master thread is used to update the current solution, while several tabu threads are used concurrently at each iteration to explore several parts of the neighborhood.

The horizon is partitioned in time intervals which are associated to a tabu thread. At each iteration, each tabu thread makes a copy of the current solution and performs a local search only on its given time interval and the bordering largest intervals considering production and demand. Then the master thread collects the moves selected by the tabu threads and applies them to the master solution. This new solution is the starting point of the next iteration.

The tabu list and diversification penalties are common to all tabu threads and updated at the end of each iteration.

In practice, the horizon start at midnight and time intervals correspond to periods of 24 hours. Since the load is lower and less variable during the night, moves overlapping time intervals are less likely to happen.

5.6 Computational results

Our approach is compared to mixed integer linear programming (MILP) in terms of objective value and solution time.

5.6.1 MILP Solution

The MILP model is derived from our model, with constraints defined in Eqs. (1)-(5.14) and objective terms in Eqs. (5.15)-(5.25). The main differences between the two models are as follows:

- generation functions are convexified and made piecewise linear, by computing function values for four values of the turbined flow and two values of the water head, and performing linear interpolation;
- objective terms are linearized, and the linear coefficients are calibrated empirically to produce similar solutions.

MILP problems are solved by CPLEX 12.7 CPLEX (2017) with heavy tuning.

5.6.2 Tabu Search Solution

For tabu search, generation functions are discretized into 12 points, and spilled flow discretization step is set to 3 m^3/s. These values result from preliminary calibration; they correspond to a compromise between solution accuracy and computational time. As stated in Hedar et Ali (2012), too many discretization points are detrimental to convergence speed.

Our system representation and tabu search procedure are implemented in F#, the functional language of the .NET environment. To emphasize the flexibility of our approach, tabu search is initiated with the most naïve solution, which consists in replicating during the whole horizon the decisions observed at the beginning of the horizon.

5.6.3 Comparisons

Comparisons with MILP were performed on 8 real instances from Hydro-Québec. There are two 10-day instances for each season of the year. Autumn and spring scenarios are characterized by high inflows and moderate electrical load. Spring inflows are very high, due to the spring freshet. Summer scenarios have moderate inflows and low demand, while winter scenarios have low inflows and very high demand. Experiments were carried out on a server with 2 processors Intel Xeon CPU E5-2690 v2 at 3.00 GHz and 256 GB of RAM.

We define the relative gap of a solution as the difference between its objective value and the dual bound calculated during MILP optimization. Fig. 5.5 represents the typical evolution of the relative gap of the best solution during the tabu search, here for instance "Autumn 1". After only 4 min of computation, the tabu search had already found a solution with a relative gap smaller than 5%.

Table 5.1 shows the time needed by MILP and tabu search to find a solution for which relative gap is less than 5% or 10%. Considering the MILP approach, the computation time is identical for both threshold values. This is because for all test cases, the first feasible solution found by CPLEX was always within a relative gap of 2%. However, it took up to 6 hours to find this solution. As for our tabu search procedure, it can always provide a solution and improve it as the search goes on. For each solution, it needed 10 minutes or less to find a solution for which the relative gap is less than 5%. This comparison shows that even with the most naïve initial solution, our approach can provide almost optimal solutions within only a very small portion of the computation time needed by CPLEX. On some instances, the proposed algorithm can be 235 times faster than CPLEX.

Differences of tabu computational time between the different scenarios can be explained by the distance between the initial solution and the optimal one. The instance with the longest tabu computational time, "Autumn 2", has been solved again with another initial solution: the operational planning of the previous day. The time to find a solution with a relative gap smaller than 5% dropped from 10 to 1 minute. In practice, starting with the last operational planning reduces significantly the computational time of tabu search. However, MILP computational time cannot be reduced, because CPLEX is not able to handle initial solutions for our problem.

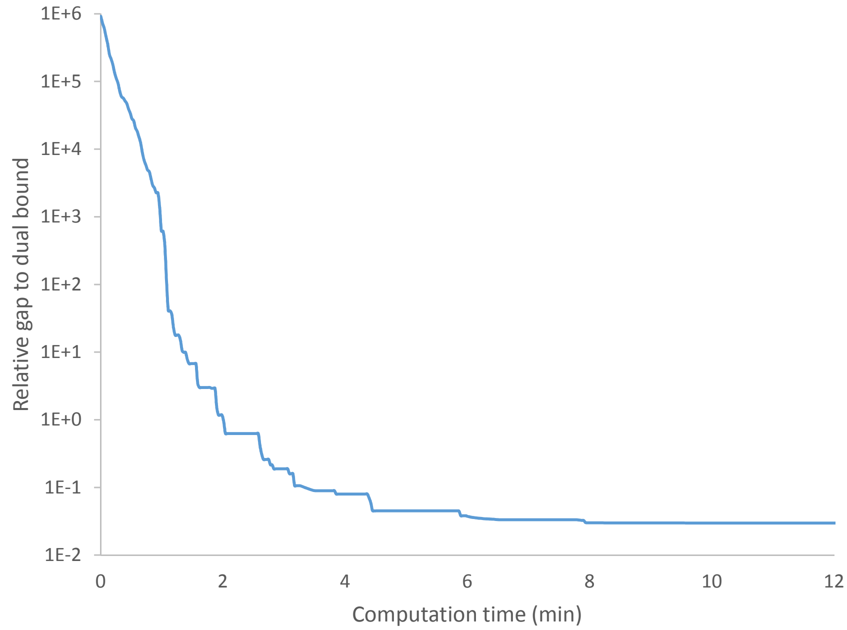

Figure 5.5 Evolution of relative gap during tabu search for instance "Autumn 1".

Table 5.1 Computation time (in min) for different relative gap thresholds

	5%		10%	
Scenario	MILP	Tabu	MILP	Tabu
Autumn 1	164	4	164	3
Autumn 2	295	10	295	4
Winter 1	63	9	63	6
Winter 2	36	7	36	5
Spring 1	115	6	115	4
Spring 2	320	4	320	3
Summer 1	330	10	330	4
Summer 2	358	2	358	2

5.7 Conclusion

This paper addresses operational concerns of short-term planners for large hydropower production systems such as Hydro-Québec. They need an adjustment tool that is very fast and flexible enough to deal with their variable environment. A mathematical representation of operational short-term planning is presented, including complex constraints such as automatic generation control. A new tabu search approach is proposed. It is based on large neighborhoods which take advantage of the problem characteristics. This search is parallelized to satisfy the operational timing. It was shown that this approach can provide planners with a solution at all time (this is similar to the "anytime" property of various algorithms; see Boddy et Dean (1994)) and find near-optimal solutions orders of magnitude faster than MILP. It is also less restrictive on the mathematical representation. While our method has been applied to a single planning environment, the one faced by Hydro-Québec, it could easily be extended to deal with other short-term hydropower planning settings, as long as the key decisions to be made revolve around the number of production units to be used at any point in time.

The key assumption upon which our method relies include the deterministic nature of future inflows and demand, the possibility to model generation functions as piecewise linear curves, and the fact that several constraints regarding the electrical network (in particular, w.r.t. its stability) are neglected. Without these assumptions, our method would be unable to produce useful short-term production schedules.

In practice, inflows and demand cannot be forecast with complete certainty. It would therefore be interesting to develop short-term planning methods capable of integrating this uncertainty and its impacts on the decision-making process.

5.8 Acknowledgements

This work was supported by NSERC/Hydro-Québec Industrial Research Chair on the Stochastic Optimization of Electricity Generation, Hydro-Québec Production, and Mitacs through the Mitacs Accelerate program. We also wish to thank the anonymous referees who reviewed this paper for their insightful comments.

CHAPITRE 6 ARTICLE 3: OPTIMIZED OPERATING RULES FOR SHORT-TERM HYDROPOWER PLANNING IN A STOCHASTIC ENVIRONMENT

Alexia Marchand[1], Michel Gendreau[1], Marko Blais[2] et Jonathan Guidi[2]

[1]Department of Mathematics and Industrial Engineering, Polytechnique Montréal, Montréal, Québec, Canada.

[2]Hydro-Québec, Montréal, Québec, Canada.

Cet article a été soumis à la revue *Computational Management Science* le 4 juillet 2018. L'article est encore en processus de révision.

Abstract To operate a large-scale hydropower production system in an ever-changing environment, operating rules are a convenient way of communication between short-term planners and real-time dispatchers. This article presents a new form of operating rules, and a solution approach to solve the short-term planning problem directly in the space of rules. Our operating rules are designed to handle complex hydro-valleys and highly constrained reservoirs. Our solution approach is based on tabu search and easily implemented. Uncertainty on inflows and electrical load is represented in the mathematical model via a 2-stage scenario tree. Numerical experiments on real instances from Hydro-Québec show that our approach is able to find good stochastic solutions while respecting the operational timing, and it improves the objective value by up to 54% in instances with moderate to high inflows.

Keywords Hydropower planning, operating rules, stochastic optimization, tabu search.

6.1 Introduction

6.1.1 Short-term hydropower planning

Hydropower planning aims at optimizing the use of hydro plants in order to maximize their efficiency during a given horizon, while satisfying the electrical load and operational constraints.

At short term, the planning horizon typically covers the next 7 to 30 days with hourly time steps. Operational constraints reflect considerations over safety, reliability, maintenance, and environment regulations compliance. The first objective behind the choice of any planning strategy is to respect these constraints, or minimize the degree to which they are violated. The second objective is to maximize production efficiency while following, as much as possible, medium-term trajectories of reservoir volumes.

The short-term planning problem may be solved in two different frameworks. The first involves what-if analyses and case studies, for instance to evaluate the cost of some equipment maintenance. The second involves operations: every day, short-term planners provide a production planning to daily planners. In this article, we will focus on the operational context.

Our work is applied to Hydro-Québec (HQ), Québec's public power utility, in particular its division Hydro-Québec Production (HQP), which manages its power generation and assets. HQP is the largest hydropower producer in North America. Hydro generation represents over 99% of its production (Hydro-Québec, 2017). HQP production system includes 63 hydro plants with an installed capacity of 37,309 MW, and 27 reservoirs totaling up to 176 TWh of storage. In 2017, it generated 205 TWh of electricity.

At HQP, short-term planners directly provide operating rules to real-time dispatchers every working day. But before sending them to the dispatchers, short-term planners must check their electrical feasibility with intra-day planners. The latter use a more accurate representation of the electrical network. If the rules do not satisfy the electrical constraints, intra-day planners send them back to short-term planners, who adjust them until they are validated by the intra-day planners. Then, they are sent to the dispatchers, who start using them the next day. This planning process is represented in figure 6.1.

6.1.2 Operating rules

When short-term planners determine operating rules for the next one to three days, there is still uncertainty within this horizon. Variability particularly concerns natural inflows

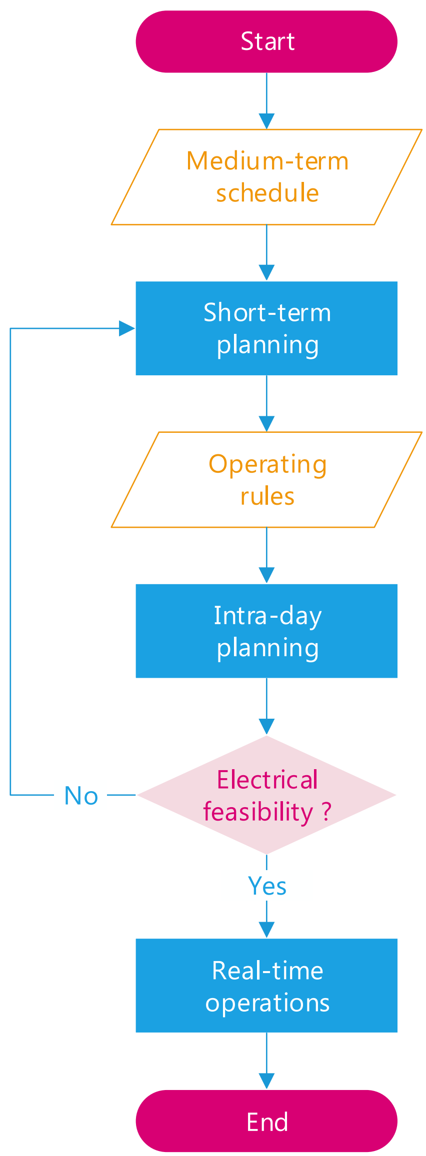

Figure 6.1 Diagram of short-term planning process.

in the reservoirs, electrical load, and outages of generating units or electrical lines. To ensure reliability and maximize efficiency, production planning must take this variability into account.

For this reason, short-term planners do not directly give the dispatchers a production planning, but rather operating rules which can provide a feasible planning for any real condition encountered.

Operating rules divide hydro plants into three categories:

- *predetermined* hydro plants have their production already fixed by medium-term planning;
- *level-constrained* hydro plants have some flexibility in their production but their upstream reservoir levels are bounded during the horizon;
- *variable* hydro plants do not have any short-term constraint on their production or their upstream reservoirs.

Hydro plants can move from one category to another, depending on the season of the year, the outages or the reservoir levels.

Predetermined hydro plants decisions correspond to a given constant production during the whole horizon, in order to satisfy medium-term goals. These goals may be, for instance, to empty the upstream reservoir before the spring freshet, or to fill it before winter.

Variable hydro plants are ordered in a priority list. In the (theoretical) case of operating rules with only variable hydro plants, the following rules will apply. Each time the electrical load is increasing, while it is not satisfied, the next generating unit to be committed belongs to the highest available hydro plant in the priority list. Conversely, whenever the load drops and needs one unit to be uncommitted, the lowest plant in the list with committed units will be chosen. It is interesting to note that the unit commitment in variable hydro plants always follows the variations of the electrical load. Short-term planners currently set priorities in order to follow reservoir volume trajectories in the medium-term planning.

Modifications of level-constrained hydro plants take precedence over variable plants when their upstream reservoir level is outside of its bounds. Moreover, if modifying the production of a variable plant implies increasing a bound violation at a neighboring level-constrained plant, then the modification is performed only if there is another modification to compensate for the violation increase.

Furthermore, each hydro plant has a minimum number of units to commit at each hour.

We will see that these operating rules are applied for each time step, without any anticipation or feedback loop.

6.1.3 Problem statement

Short-term planners currently determine operating rules by trial and error in a deterministic scenario. However, real load and inflows can significantly diverge from their forecasts, especially on weekends when the rules are not updated. Thus, rules may become inadequate to the real situation and prevent last-minute transactions on the electricity market. Therefore, considering uncertain inflows and electrical load in short-term planning is essential to maximize utility profits.

The objective of this article is to simulate operating rules, and to select a set of rules to maximize efficiency. We also consider uncertainty in variable inflows and electrical load during the third day of the horizon.

6.1.4 Literature review

The short-term hydropower planning problem has been thoroughly studied during the last decade, both in its deterministic and stochastic forms. Many mathematical models and solution approaches exist; they are classified in literature review by van Ackooij *et al.* (2018).

Only a small proportion of solution approaches are based on operational rules. These approaches use priority lists, which have been introduced in 1959 by Baldwin *et al.* (1959). The main advantage of priority lists is their compactness. Thus, they are easily transmitted between planners and operators. Moreover, they are easily applied by real-time operators, even when real conditions are different from the forecast.

However, to the best of our knowledge, short-term hydropower optimization has never been performed directly in the space of operating rules (or priority lists). Rules are either used for simulation in decision support systems (see the survey by Karimanzira (2016) for more details), or to generate an initial production planning, which will then be optimized (Guan *et al.*, 1992) or adjusted with different heuristics (Senjyu *et al.*, 2003; Amiri et Khanmohammadi, 2013; Moradi *et al.*, 2015; Quan *et al.*, 2015).

Priority list optimization is a permutation problem with a small number of variables. However, if n is the number of variables, the number of possible permutations is $n!$. Hence, exhaustive enumeration is not a suitable approach. Metaheuristic methods have proved effective to find good solutions to complex combinatorial problems in a wide range of fields (Gendreau et Potvin, 2010a). Some of the most common ly used metaheuristic approaches are genetic algorithms (Holland, 1973), simulated annealing (Kirkpatrick *et al.*, 1983), tabu search (Glover, 1989), and ant colony optimization (Dorigo *et al.*, 2006).

Uncertainty is commonly represented in four different ways. One simple way is to add bounds: reservoir volume bounds to hedge against variability in natural inflows, and reserve constraints to hedge against uncertainty in electrical load. Bounds avoid additional complexity in the model, but they need calibration and may lead to suboptimal scheduling. Other representations of uncertainty are explicit: robust optimization (Liu et Tomsovic, 2015), chance-constrained optimization (van Ackooij *et al.*, 2014), and scenario trees (Séguin *et al.*, 2017). Robust optimization ensures feasibility within a given uncertainty set. Chance-constrained optimization involves that constraints may only be respected with some given probability. Both robust and chance-constrained optimization need calibration to define the uncertainty set or the probability threshold of feasibility; this is a difficult task in practice. Scenario trees are the simplest explicit representation of uncertainty: they discretize the distribution of random events at different stages along the horizon. Hence, the stochastic problem can be converted to a (larger) deterministic problem. The quality of the stochastic solution depends on the form of the scenario tree (Keutchayan *et al.*, 2017). Two stages are enough in our case, because operating rules are not anticipative.

6.1.5 Our approach

This article proposes a novel definition of operational rules for short-term hydropower planning, based on priority lists. The planning problem is directly optimized in the space of rules via tabu search. Moreover, uncertainty in natural inflows and electrical demand is represented with a scenario tree during the third day of the horizon.

6.2 Mathematical model of a production planning

The following mathematical model is based on Marchand *et al.* (2018a).

6.2.1 Notation

Sets and indices

$1..T$	Set of time steps, indexed by t
R	Set of reservoirs, indexed by r
S	Set of river sections, indexed by s
S^up_r, S^dn_r	Set of river sections directly upstream or downstream of reservoir r
C	Set of hydro plants, indexed by c
C^{AGC}, C^{stb}	Set of hydro plants participating or not in automatic generation control (AGC)
C^up_s	Set of hydro plants directly upstream of river section s
D	Set of spillways, indexed by d
D^up_s	Set of spillways directly upstream of river section s
Z	Set of electrical zones, indexed by z
E_z	Set of hydro plants associated with electrical zone z
L	Set of electrical links, indexed by l
L^in_z, L^out_z	Set of electrical links upcoming to or outgoing from zone z

Parameters

$\alpha^{prop}_{s,t'}$	Proportion of water outgoing from river section s after t' time steps
τ_s	Maximum water delay (in time steps) in river section s
$i_{r,t}$	Natural inflows in reservoir r during time step t (m^3/s)
γ^{conv}_t	Conversion factor from flow to volume during time step t ((hm^3)/(m^3/s))
$l^{up}_c(.)$	Upstream level of hydro plant c, depending on its upstream reservoir volume (m)
$l^{dn}_c(.)$	Downstream level of hydro plant c, depending on the incoming flow to its downstream river section (m)
$g_{c,t}(.)$	Power production of hydro plant c, depending on its number of committed units, turbined flow and water head (MW)
$g^{min}_{c,t}(.), g^{max}_{c,t}(.)$	Minimum and maximum feasible power production at hydro plant c, depending on its number of committed units and water head (MW)
$\delta_{z,t}$	Net electrical load in zone z during time step t (MW)
ϵ^{loss}_l	Loss coefficient in electrical link l
$b^{src}(.), b^{dest}(.)$	Power upcoming to link source or outgoing from link destination, depending on transited power in link (MW)
ω_r	Water value in reservoir r (MWh/hm^3)

Decision variables

$n_{c,t}$	Number of committed units in hydro plant c during time step t
$q_{c,t}$	Turbined flow in hydro plant c during time step t (m^3/s)
$w_{d,t}$	Spilled flow in spillway d during time step t (m^3/s)

Other variables

$u_{s,t}, o_{s,t}$	Water flow upcoming to and outgoing from river section s during time step t (m^3/s)
$v_{r,t}$	Water volume in reservoir r at the end of time step t (hm^3)
$h_{c,t}$	Water head of hydro plant c during time step t (m)
$p_{c,t}$	Power production of hydro plant c during time step t (MW)
$b_{l,t}$	Power transmitted through link l during time step t (MW)
$e_{z,t}$	Difference between production and load in zone z during time step t (MW)
d_t^{AGC}	Load to be satisfied by AGC plants during time step t (MW)
y_t^{AGC}	Production rate of AGC plants during time step t (MW/(m^3/s))
$p_{c,t}^{min}, p_{c,t}^{max}$	Minimum and maximum feasible power production of hydro power c during time step t (MW)
$f_{s,t}$	Water volume in transit in river section s at the end of time step t (hm^3)
$s_{r,t}$	Potential energy stock in reservoir r at the end of time step t (MWh)

6.2.2 System dynamics

The hydraulic network is formed of reservoirs with hydro plants and spillways, and river sections between reservoirs. The electrical network is composed of electrical zones and links. Each hydro plant is associated with an electrical zone. The system dynamics is represented by the following equations:

$$u_{s,t} = \sum_{c \in C^u p_s} q_{c,t} + \sum_{d \in D^u p_s} w_{d,t} \qquad \forall s, \forall t \tag{6.1}$$

$$o_{s,t} = \sum_{t'=0}^{\tau_s} \alpha^{prop}_{s,t'} . u_{s,t-t'} \qquad \forall s, \forall t \tag{6.2}$$

$$v_{r,t} = v_{r,t-1} + \gamma^{conv}_t . (i_{r,t} + \sum_{s \in S^u p_r} o_{s,t} - \sum_{s \in S^d n_r} u_{s,t}) \qquad \forall r, \forall t \tag{6.3}$$

$$h_{c,t} = l^{up}_c(v_{r^u p_c,t}) - l^{dn}_c(u_{s^d n_c,t}) \qquad \forall c, \forall t \tag{6.4}$$

$$p_{c,t} = g_{c,t}(n_{c,t}, q_{c,t}, h_{c,t}) \qquad \forall c, \forall t \tag{6.5}$$

$$b^{src}(b_{l,t}) = \begin{cases} b_{l,t} & \text{if } b_{l,t} \geq 0 \\ (1 - \epsilon^{loss}_l) b_{l,t} & \text{otherwise} \end{cases} \tag{6.6}$$

$$b^{dest}(b_{l,t}) = \begin{cases} (1 - \epsilon^{loss}_l) b_{l,t} & \text{if } b_{l,t} \geq 0 \\ b_{l,t} & \text{otherwise} \end{cases} \tag{6.7}$$

$$e_{z,t} = \sum_{c \in E_z} p_{c,t} + \sum_{l \in L^i n_z} b^{dest}(b_{l,t}) + \sum_{l \in L^o ut_z} b^{src}(b_{l,t}) - \delta_{z,t} \qquad \forall z, \forall t \tag{6.8}$$

$$d^{AGC}_t = \sum_{z \in Z} \delta_{z,t} - \sum_{c \in C^{stb}} p_{c,t} \qquad \forall t \tag{6.9}$$

$$p^{min}_{c,t} = g^{min}_{c,t}(n_{c,t}, h_{c,t}) \qquad \forall c, \forall t \tag{6.10}$$

$$p^{max}_{c,t} = g^{max}_{c,t}(n_{c,t}, h_{c,t}) \qquad \forall c, \forall t \tag{6.11}$$

$$y^{AGC}_t = \begin{cases} 0 & \text{if } d^{AGC}_t \leq \sum_{c \in C^{AGC}} p^{min}_{c,t} \\ 1 & \text{if } d^{AGC}_t \geq \sum_{c \in C^{AGC}} p^{max}_{c,t} \\ \frac{d^{AGC}_t - \sum_{c \in C^{AGC}} p^{min}_{c,t}}{\sum_{c \in C^{AGC}} (p^{max}_{c,t} - p^{min}_{c,t})} & \text{otherwise} \end{cases} \qquad \forall t \tag{6.12}$$

$$p_{c,t} = (1 - y^{AGC}_t) . p^{min}_{c,t} + y^{AGC}_t . p^{max}_{c,t} \qquad \forall c \in C^{AGC}, \forall t \tag{6.13}$$

$$q_{c,t} = (g_{c,t})^{-1} (n_{c,t}, p_{c,t}, h_{c,t}) \qquad \forall c \in C^{AGC}, \forall t \tag{6.14}$$

Water conservation is represented by equations 6.1-6.3. Equations 6.1 and 6.2 define the water flow upcoming to and outgoing from river sections. Equation 6.3 calculates the reservoir volumes at the end of each time step.

Power generation is represented by equations 6.4 and 6.5. Equation 6.4 defines the water head of hydro plants. There is no restriction in the definition of level functions $l^{up}_c(.)$ and $l^{dn}_c(.)$. In our case, they are modeled with piecewise linear functions because this modeling is accurate enough. Equation 6.5 represents power production in hydro plants. The representation of generation functions is not limited either. At HQP, they are analytical functions.

Energy conservation is represented by equations 6.6-6.8. Equations 6.6 and 6.7 calculate the relative values of power upcoming to the source zone and outgoing from the destination zone of a given link, depending on the relative value of power transmitted through the link. Equation 6.8 defines the differences between production and load in zones.

Equations 6.9-6.14 represent the automatic generation control (AGC), to which HQP production system is submitted. Some plants are tagged as part of the AGC; they all have the same production rate at each time step. Moreover, within the limits of their generation functions, they produce the difference between the total electrical load and the production of the other plants. Hence, it is important to note that turbined flows in AGC plants are not decisions, but rather adjustment variables.

Equation 6.9 calculates the electrical load to be satisfied by plants participating in AGC. Equations 6.10 and 6.11 represent minimum and maximum feasible power production in hydro plants. Equation 6.12 gives the production rate of AGC plants. Equations 6.13 and 6.14 define the power production and the turbined flow in AGC plants.

6.2.3 Objective

The objective to be minimized obj^{glob} is the weighted sum of four terms (obj^{v}, obj^{dem}, obj^{eff}, and obj^{s}) which are defined in the following paragraphs.

$$obj^{glob} = \lambda^{v}.obj^{v} + \lambda^{dem}.obj^{dem} + \lambda^{eff}.obj^{eff} + \lambda^{s}.obj^{s} \tag{6.15}$$

where λ^{v}, λ^{dem}, λ^{eff}, and λ^{s} are user-defined weights.

Level bound violations Bounds on decision variables are always satisfied when applying the rules. However, reservoirs may violate some volume constraints.

Reservoirs have their volume bounded by three different types of constraints (which imply different behaviors when applying the operating rules). They are defined as follows, from the loosest to the most constraining:

1. $v_{r,t}^{alt,min}$ and $v_{r,t}^{alt,max}$, minimum and maximum *alert-level* bounds;
2. $v_{r,t}^{sht,min}$ and $v_{r,t}^{sht,max}$, minimum and maximum *short-term* bounds;
3. and $v_{r,t}^{op,min}$ and $v_{r,t}^{op,max}$, minimum and maximum *operating* bounds.

Bound violations are quadratically penalized and weighted by a factor depending on the bound type. The objective term obj^v represents bound violations and is defined as follows:

$$obj^v = \sum_{b \in \{alt,sht,op\}} \sum_{r \in R} \sum_{t=1}^{T} \gamma^b (\max(v_{r,t} - v_{r,t}^{b,max}, v_{r,t}^{b,min} - v_{r,t}, 0))^2 \tag{6.16}$$

where γ^{alt}, γ^{sht} and γ^{op} are user-defined factors.

Load satisfaction The load satisfaction objective term obj^{dem} is the sum of the quadratic differences between production and load at each electrical zone and each time step:

$$obj^{dem} = \sum_{t=1}^{T} \sum_{z \in Z} e_{z,t}^2 \tag{6.17}$$

Efficiency The efficiency objective term obj^{eff} is defined as the value of water released from reservoirs during the horizon.

$$f_{s,t} = f_{s,t-1} + \gamma_t^{conv}.(u_{s,t} - o_{s,t}) \qquad \forall s, \forall t \tag{6.18}$$

$$s_{r,t} = \omega_r.(v_{r,t} + \sum_{s \in S^u p_r} f_{s,t}) \qquad \forall r, \forall t \tag{6.19}$$

$$s_{r,T}^{sup} = s_{r,-1} + \omega_r.\gamma_t^{conv}.\sum_{t=1}^{T} i_{r,t} \qquad \forall r \tag{6.20}$$

$$obj^{eff} = \sum_{r \in R} (s_{r,T}^{sup} - s_{r,T}) \tag{6.21}$$

Equation 6.18 describes the dynamics of water volume transiting through river sections. Equation 6.19 defines the value of water stored in reservoirs. Equation 6.20 gives the final value of water in reservoirs at the end of the horizon if no water is released during the whole horizon. Equation 6.21 defines the value of released water during the horizon.

Start-ups and shut-downs In the objective term obj^s, variations of the number of committed units are penalized for each plant:

$$obj^s = \sum_{t=1}^{T} \sum_{c \in C} |n_{c,t} - n_{c,t-1}| \tag{6.22}$$

where $|.|$ represents the absolute value function.

6.3 Simulation and evaluation of operating rules

We define a scenario as a given set of series representing natural inflows and electrical load. For a given scenario, our simulation algorithm converts any set of rules into a production planning, which can be evaluated with the global objective value.

When several scenarios are taken into account, we define the objective value of a given set of rules as the expectation of the simulated global objective value over the set of scenarios.

6.3.1 Simulation algorithm

Simulation along the horizon

For each time step of the horizon, from the beginning to the end, the following steps are applied:

1. Set decision variables as for preceding time step.
2. Generate list of possible modifications, as described in section 6.3.1.
3. Test modifications in the list until one improves the global objective value. If such an adjustment is found, return to step 2.

List of possible modifications

Modifications are defined as a variation of a decision variable at the given time step. Modifications on the number of committed units correspond to a variation of 1 on the corresponding variable value. Turbined flow variables of hydro plants in C^{stb} and spilled flow variables are discretized as in Marchand *et al.* (2018a). Hence, modifications on these variables imply passing to the next discretization point.

At a given time step, our list of potential modifications is composed of 6 sub-lists. They are defined and ordered in the following way:

1. to satisfy alert-level bounds in level-constrained reservoirs;
2. to bring hydro plants production closer to their optimal point;
3. to satisfy the total load;
4. to force satisfaction of the total load, ignoring bounds of level-constrained reservoirs;
5. to force satisfaction of short-term bounds in level-constrained reservoirs;
6. and to force spilling at reservoirs violating their maximum operating bound.

Modifications of type 1-5 involve the number of committed units in a hydro plant, or the turbined flow at a hydro plant in C^{stb}. Modifications of type 6 involve the flow in a spillway.

In each sub-list, modifications involving variable hydro plants are prioritized and ranked, depending on the plant position in the variable priority list.

Testing modifications

A modification may involve other modifications if it increases a bound violation in a neighboring level-constrained reservoir. These adjustment modifications are always of type 1.

Application of a modification is always followed by the adjustment of the power transmission variables in the electrical links, via a simple minimum-cost flow problem (Ahuja *et al.*, 1989).

A modification is accepted only if it improves the global objective value. Moreover, it cannot increase bound violations in level-constrained reservoirs (except for type 4), and it must always be in the same direction as total load variations (except for type 5).

Modifications of the list defined in section 6.3.1 are tested until one is accepted. Then, a new list of possible modifications is generated, and so forth. The algorithm stops when there is no acceptable modification in the last generated list.

The global simulation algorithm is represented with flow charts in figures 6.2, 6.3 and 6.4. Figure 6.2 is a flow chart of the global algorithm. It refers to an algorithm to find an accepted modification, which is represented in figure 6.3. The latter refers to an algorithm to test modifications in figure 6.4.

6.3.2 Scenario generation : modeling the uncertainty

We represent the variability of inflows and load during the third day of the horizon.

We define the forecast error of a stochastic variable as the difference between the observed value and the forecast value 3 days before. The forecast error has been studied for the inflows at each reservoir and the total electrical load during the last 2 years. For each stochastic variable, the mean is very close to zero because it is already considered in the forecast value. However, the standard deviation varies depending on the season of the year. For each reservoir and for the total load, standard deviation values are normalized with respect to the forecast value and aggregated by month.

Reservoirs are partitioned into subsets, where all reservoirs of a subset are expected to receive correlated inflows. This partition is the result of an in-house study at HQP. Each subset of reservoirs R_v is associated with a random variable Ω_v. These variables are assumed

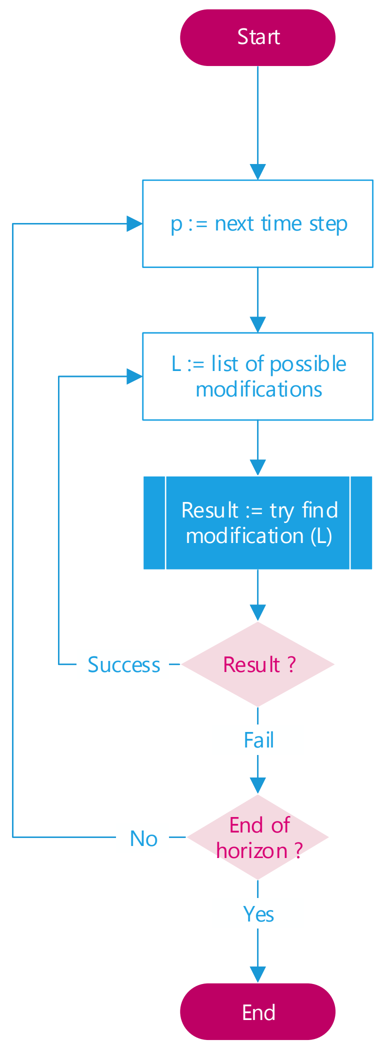

Figure 6.2 Diagram of algorithm to apply rules.

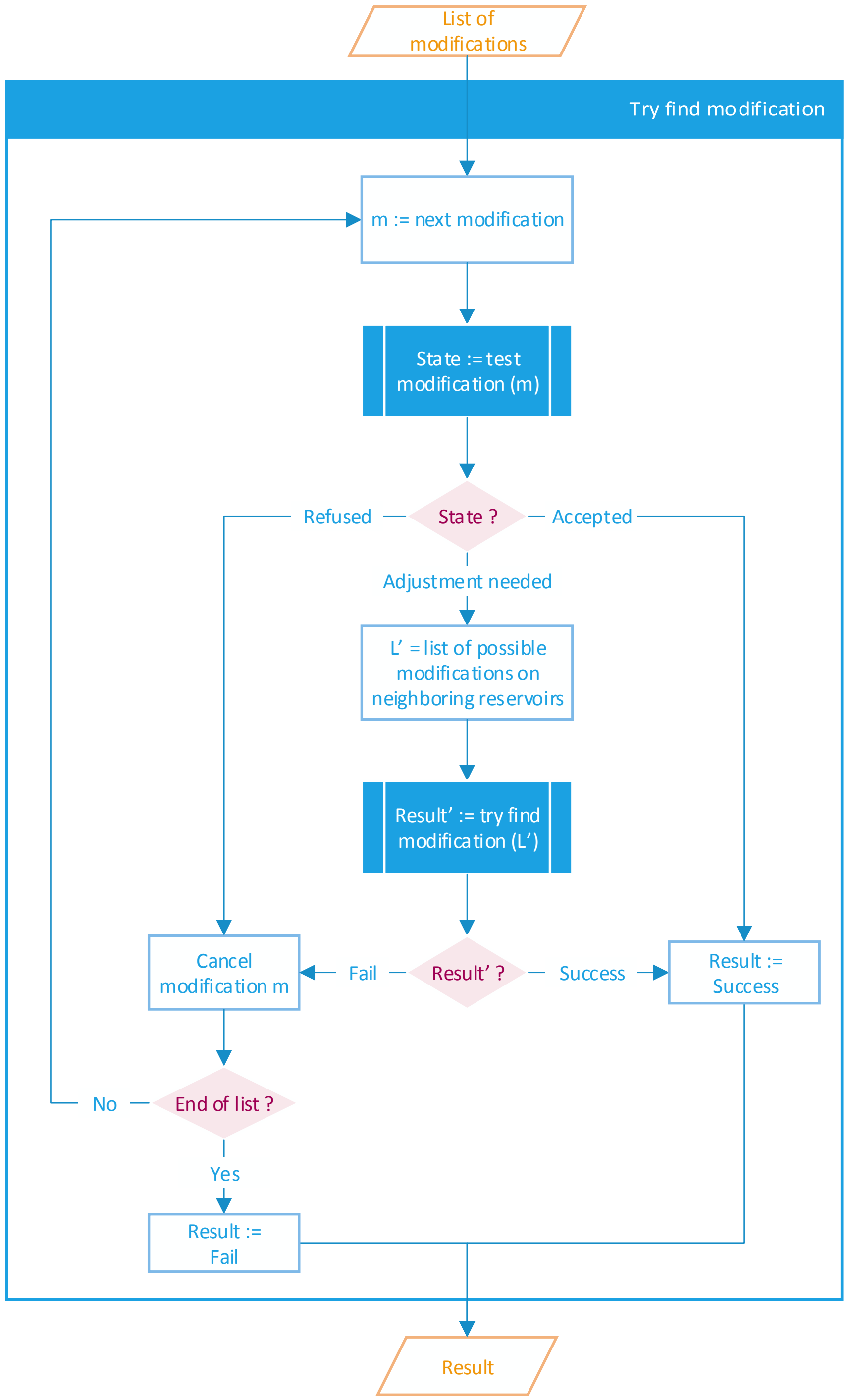

Figure 6.3 Diagram of algorithm to find modification.

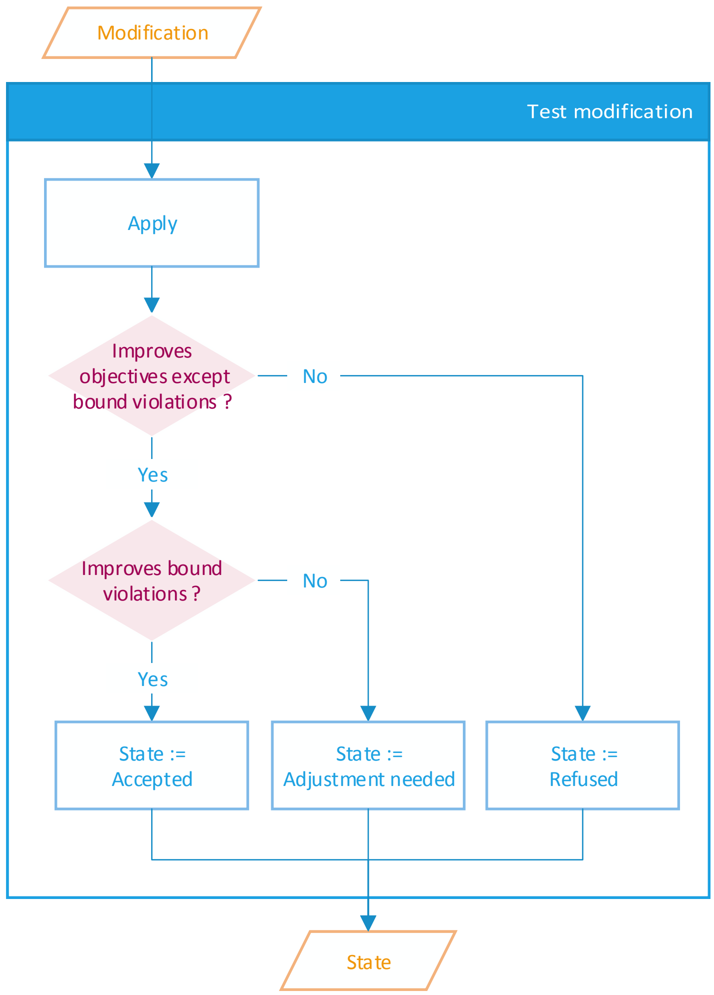

Figure 6.4 Diagram of algorithm to test modification.

independent and following a standard normal distribution.

Then for each sample ω_v of each random variable Ω_v, for each reservoir r in R_v and each time step t in the third day of the horizon, we replace the forecast value $i_{r,t}$ by the following calculation:

$$i_{r,t} \leftarrow i_{r,t}.(1 + \omega_v.\sigma_r) \tag{6.23}$$

where σ_r is the normalized standard deviation of the forecast error in reservoir r.

We consider an additional random variable Ψ to account for the uncertainty on the total exchanges on the electricity market. The standard deviation of the forecast error is estimated as for the inflows and the same calculation is performed for each sample.

Scenarios are generated with a standard multivariate normal distribution, in order to sample all variables simultaneously.

It is important to note that the simulation algorithm can be computed in parallel for each scenario, because scenarios are mutually independent. Increasing the number of generated scenarios improves the evaluation accuracy of operating rules, but it may increase the computation time as well. Hence, the number of generated scenarios is a compromise between accuracy and computation capacity. In our case, experiences showed that 30 scenarios are accurate enough and involve acceptable computation time.

6.4 Optimization of rules

The priority list of variable plants is optimized with tabu search embedded into a variable neighborhood search framework.

6.4.1 Tabu search

Solutions are characterized by the order of the priority list for variable plants. Whenever a solution is visited during the search, it is tagged as tabu during η iterations, where η is a random number between user-defined parameters η^{min} and η^{max}.

Our local search is a first-improvement search on a 2-opt neighborhood. This neighborhood contains all solutions resulting from a swap between two consecutive plants in the current solution.

Neighboring solutions are randomly sorted and consecutively evaluated via our operating rules simulator, until one is accepted. A solution is accepted if it is non-tabu and it improves the current objective value, or if it improves the best-found objective value. This is the aspiration criterion.

If no move is accepted during the neighborhood search, then the non-tabu solution with the minimal objective value is accepted.

6.4.2 Variable neighborhood search

To enhance diversification during the search, tabu search is embedded into a variable neighborhood search (VNS) framework.

We define a k-order move as a swap in the priority list between two hydro plants which are separated by $k-1$ hydro plants.

The VNS algorithm is the following :

1. Initialization : $k := 2$. Choose initial solution.
2. Search : While termination criterion is not satisfied, do:
   (a) Diversification: Apply random k-order move from the best-known solution.
   (b) Intensification: Continue tabu search from diversification solution, until the best-known objective value is not improved during the last μ iterations.
   (c) If the best-known objective value is not improved during intensification and $k < k^{max}$, then $k := k+1$. Otherwise, $k := 2$.

μ and k^{max} are user-defined parameters. The termination criterion may be defined by a maximal number of iterations, or by maximal computational time.

6.5 Computational experiments

The simulator and the solution approach were implemented in F#, the functional programming language of the .NET environment. They have been tested on 5 real HQP instances with a 3-day horizon for each season of the year. Natural inflows are typically high and volatile in spring and autumn instances, while they are moderate during summer, and low during winter. The electrical load is typically high during winter, moderate during spring and autumn, and low during summer.

Our solution approach was implemented with the following parameters: $\eta^{min} = 6$, $\eta^{max} = 10$, $\mu = 10$, and $k^{max} = 10$. These values have been calibrated via a trial-and-error process. Initial solutions were chosen arbitrarily. The stopping criterion is a maximum computational time of one hour.

Deterministic and stochastic optimization are compared in terms of objective value. However, our scenario tree generation and solution method have random components. To present stable results, each instance was optimized 10 times. For stochastic optimization, a new scenario tree of 30 scenarios was generated at each optimization. Moreover, for each optimization, the stochastic objective value of the final solution was evaluated on another scenario tree with 100 scenarios. Presented results are average values over these 10 optimizations.

Experiments were carried out on a server with 2 processors Intel Xeon CPU E5-2690 v2 at 3.00 GHz and 256 GB of RAM. For stochastic optimization, operating rules were simulated in parallel on 4 threads.

The average objective value obtained by stochastic optimization is only 0.3% better than deterministic optimization. This is due to the increased computational time of simulation over the scenario tree, which reduces the number of tabu search iterations. Simulation takes on average 5 seconds over a deterministic scenario, and 90 seconds over a scenario tree.

To overcome this problem, we developed a hybrid approach, which uses deterministic optimization during the first 150 iterations, then stochastic optimization. This approach improves the average objective value by 6.4%.

Table 6.1 gives the average objective value of each solution approach on each instance, as well as the objective value variations of the stochastic and hybrid approaches compared to the deterministic approach. The best objective values are written in bold.

The hybrid approach provides very good results, except for winter scenarios. This can be explained by the low volume and variability of inflows during this season. Hence, volume bounds are less likely to be violated with the deterministic approach. For other seasons, the average objective value is improved by 11.1%.

Figure 6.5 shows the evolution of the deterministic and stochastic objective values during one hybrid optimization of instance "Spring 2". The vertical bar represents the beginning of stochastic optimization. This chart shows the necessity of stochastic optimization on risky scenarios: improvement on the deterministic objective value is not associated with improvement on the stochastic objective value.

This observation is explained by figure 6.6, which represents the volume trajectory of a small reservoir in the deterministic scenario of instance "Autumn 4", depending on the solution approach. The deterministic approach leads to a solution where the reservoir volume comes near the maximum bound on the third day. However, the stochastic and hybrid approaches lead to a more conservative volume trajectory, which avoids bound violations in scenarios with high inflows.

Table 6.1 Detailed results of global objective value.

	Objective value			Variation	
Instance	Deterministic	Stochastic	Hybrid	Stochastic	Hybrid
Spring 1	**1 500**	1 598	1 583	6%	6%
Spring 2	3 260	1 698	**1 579**	-48%	-52%
Spring 3	1 189	1 222	**1 170**	3%	-2%
Spring 4	1 679	1 336	**1 307**	-20%	-22%
Spring 5	1 857	1 690	**1 612**	-9%	-13%
Summer 1	3 579	4 163	**3 552**	16%	-1%
Summer 2	3 834	**3 618**	3 842	-6%	0%
Summer 3	**1 149**	1 633	1 182	42%	3%
Summer 4	1 129	**1 099**	1 101	-3%	-2%
Summer 5	1 317	1 080	**977**	-18%	-26%
Autumn 1	835	894	**834**	7%	0%
Autumn 2	785	836	**772**	6%	-2%
Autumn 3	**1 003**	1 065	1 034	6%	3%
Autumn 4	2 523	**1 041**	1 156	-59%	-54%
Autumn 5	843	803	**798**	-5%	-5%
Winter 1	2 322	**2 176**	2 258	-6%	-3%
Winter 2	1 706	1 707	**1 705**	0%	0%
Winter 3	**2 929**	3 995	3 071	36%	5%
Winter 4	**1 606**	1 976	1 986	23%	24%
Winter 5	**1 611**	1 949	1 840	21%	14%

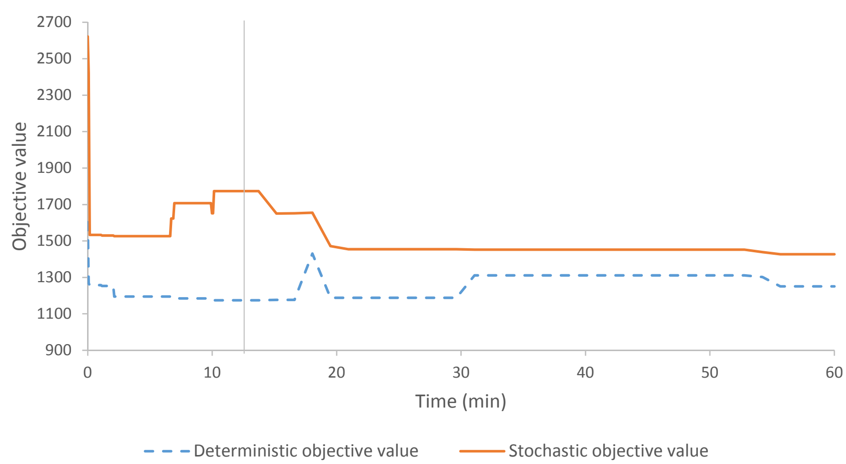

Figure 6.5 Evolution of objective value during hybrid optimization of instance "Spring 2".

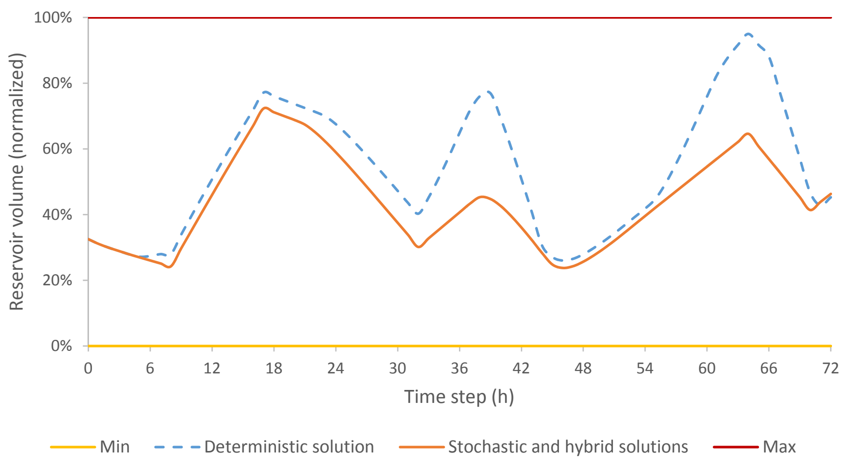

Figure 6.6 Different volume trajectories on a small reservoir in scenario "Autumn 4".

6.6 Conclusion

Operating rules are a compact and effective way to deal with uncertainty in short-term planning. This article presents a new form of operating rules for hydropower production systems, and a solution approach to optimize these rules. Our method is based on tabu search, where rules are evaluated on a scenario tree. Uncertainty is represented in the electrical load and natural inflows. Computational results on real instances from Hydro-Québec show that stochastic optimization is useful for risky scenarios, especially during spring and autumn. However, it must be started with deterministic optimization to give good results in operational timing. This hybrid approach improves the average objective value by 11% on scenarios of the spring, summer and autumn seasons. Future work will focus on a better characterization of risk in scenarios.

6.7 Acknowledgements

This work was supported by NSERC/Hydro-Québec Industrial Research Chair on the Stochastic Optimization of Electricity Generation, Hydro-Québec Production, and Mitacs through the Mitacs Accelerate program.

CHAPITRE 7 DISCUSSION GENERALE

La méthode de décomposition en trois phases présentée dans le chapitre 4 permet de calculer très rapidement des plans de production quasi-optimaux à partir d'un modèle PLNE. Les tests, réalisés sur des scénarios d'Hydro-Québec, montrent qu'elle fournit des solutions en moins de 2,5 min avec un saut de dualité inférieur à 0,03 %. Comparée aux solveurs génériques, notre méthode réduit le temps de calcul de plus de 93 %. De plus, on note de faibles violations des contraintes liantes dans la solution des sous-problèmes. Cela indique que les valeurs duales obtenues par la relaxation linéaire sont suffisamment précises. Finalement, notre méthode répond aux critères de précision et de rapidité nécessaires à la réalisation d'études d'impact dans un contexte opérationnel.

Toutefois, le modèle PLNE ne prend pas en compte toutes les contraintes opérationnelles, notamment le réglage fréquence-puissance et la non-linéarité des fonctions de production. C'est ce qui est fait dans le modèle présenté dans le chapitre 5. Ce problème plus complexe est alors résolu à l'aide d'une recherche tabou en parallèle, qui devient efficace grâce à ses voisinages larges. Sur des scénarios de 10 jours d'Hydro-Québec, notre recherche tabou initiée avec la solution la plus naïve possible parvient à de très bonnes solutions (moins de 5 % de l'optimum) en moins de 10 minutes. Ce temps de calcul descend à 1 minute lorsque la recherche tabou est initiée à partir du dernier plan de production calculé. De plus, contrairement à la résolution du PLNE par un solveur générique, la recherche tabou peut fournir solution réalisable en tout temps. Ainsi, notre approche répond bien aux besoins, parfois urgents, de la planification opérationnelle.

Les modèles mathématiques présentés dans les chapitres 4 et 5 considèrent un très grand nombre de variables de décision. Ces variables de décision doivent être réajustées à chaque variation dans les données. Or, à court-terme, il existe toujours de l'incertitude sur les apports naturels aux réservoirs, la demande électrique, la disponibilité de l'équipement, etc. Une telle modélisation demanderait donc de réajuster le plan de production en continu afin qu'il soit utilisable par les opérateurs en temps réel. Afin de garder le processus de planification court-terme/temps-réel simple et robuste, nous proposons dans le chapitre 6 une modélisation des décisions sous forme de règles de gestion.

Ces règles de gestion sont évaluées sur un peigne de scénarios de demande électrique et d'apports dans les réservoirs, et optimisées à l'aide d'une recherche tabou. Pour rester dans des temps opérationnels, nous montrons qu'il est nécessaire d'initier l'optimisation sur le scénario déterministe. Ainsi, la prise en compte de l'incertitude permet d'améliorer la valeur objectif moyenne de 11 % sur les saisons avec des apports variables : le printemps, l'été et l'automne.

CHAPITRE 8 CONCLUSION ET RECOMMANDATIONS

Dans cette thèse, nous avons présenté différents modèles et méthodes de résolution du problème de planification court-terme pour des systèmes hydroélectriques de grande taille. Ce problème étant très complexe à résoudre dans des temps opérationnels, nous nous sommes efforcés d'en exploiter la structure. Cela nous a permis à la fois de réduire la taille des modèles et d'accélérer la résolution. Nous avons développé deux nouveaux modèles et trois nouvelles méthodes de résolution afin de répondre aux différents besoins de la planification court-terme.

Ces modèles et méthodes de résolution sont aujourd'hui utilisés par Hydro-Québec Production pour gérer les opérations d'un parc de production valant plus de 31 G$, ayant généré 194 TWh en 2017 et pouvant fournir une puissance de pointe de plus de 42 000 MW. Pour les analyses d'impact, la méthode de décomposition du chapitre 4 a entraîné d'autres expérimentations ; une version plus robuste et plus rapide est actuellement en production. Pour la planification opérationnelle, le simulateur de règles de gestion est utilisé quotidiennement. La méthode d'ajustement du chapitre 5, ainsi que la méthode d'optimisation des règles du chapitre 6, sont en cours d'adaptation pour être mises en production.

Notre simulateur de règles de gestion a rendu la planification court-terme d'Hydro-Québec Production beaucoup plus rapide et robuste. Les planificateurs ont désormais le temps d'analyser et d'améliorer leurs plans de production. Cette amélioration est aujourd'hui possible, grâce aux méthodes d'optimisation développées dans cette thèse.

Les outils de programmation mathématique pourront aider les planificateurs à faire face à des situations exceptionnelles, pour lesquels les heuristiques anciennement utilisées n'auraient pas trouvé de solution. Ils permettent aussi de valider a posteriori le travail réalisé en planification.

De plus, les modèles d'optimisation formalisent les objectifs de la planification court-terme, rendant possible la mesure de la performance du processus. Le suivi de cette mesure permettra l'amélioration en continu de ce processus.

Notons enfin qu'Hydro-Québec montre un intérêt à l'adaptation et à la mise en production des méthodes développées dans cette thèse pour réaliser la planification à très court terme.

8.1 Limitations de la solution proposée

Dans nos modèles, les fonctions de production sont présentées par nombre de groupes engagés dans les centrales, en supposant que le prochain groupe à être engagé est toujours le meilleur disponible. Cette modélisation a pour avantages de réduire considérablement la taille du problème et d'être suffisamment précise dans la majorité des cas. Cependant, il existe des contraintes électriques qui lient des groupes turbine-alternateur en particulier. Notre modélisation ne permet pas de considérer ces contraintes directement. De plus, pour éviter des dégradations dans les équipements, les groupes ne peuvent pas être opérés dans certaines plages de débit. Ces plages de débit interdites entraînent des discontinuités dans les fonctions de production, qui ne sont pas prises en compte dans cette thèse.

Le réseau électrique est représenté très simplement dans nos modèles. Nous prenons en compte des limites de transit et des taux de pertes constants sur les liens électriques. Or, en pratique, les limites et les pertes sont variables : elles dépendent notamment de la puissance transitée, de la température et du taux d'humidité. De plus, il existe de nombreuses autres contraintes qui modifient le comportement du système de production. C'est le cas par exemple des différents types de réserves, qui contraignent la production de différents ensembles de groupes turbine-alternateur.

Les violations de contraintes non prises en compte dans les fonctions de production et le réseau électrique peuvent être facilement évaluées à la fin de l'optimisation. Elles pourraient ensuite être corrigées à l'aide d'heuristiques. Pour prendre en compte ces contraintes directement dans l'optimisation, nos méthodes de résolution nécessiteraient des ajustements.

Le modèle mathématique présenté dans les chapitres 5 et 6 peut entraîner des solutions sous-optimales. En effet, les transits dans les liens électriques sont ajustés une fois la production des centrales fixée, mais les limites de transit empêchent parfois la production d'être entièrement acheminée dans les zones de demande. Ces situations sont pénalisées par les écarts entre la production et la demande dans chaque zone, mais nous ne proposons pas de solution pour y remédier. Une heuristique d'ajustement serait sûrement bienvenue.

Enfin, l'incertitude sur les apports et la demande est modélisée très simplement dans le chapitre 6. Faute de connaissance sur la nature de cette incertitude, nous supposons que les variables aléatoires suivent des lois normales et qu'elles sont indépendantes entre elles. Une meilleure modélisation permettrait d'obtenir des résultats plus précis sans changement dans la méthode de résolution.

8.2 Améliorations futures

En plus des ajustements proposés dans la section précédente, nous proposons ici des voies d'amélioration pour chacun des contextes de planification.

Pour les analyses d'impact, le modèle et la méthode du chapitre 4 pourrait être ajustés pour intégrer les contraintes opérationnelles, telles que le réglage fréquence-puissance.

Pour la validation du plan de production moyen-terme, les règles de gestion pourraient inspirer d'autres voisinages qui accéléreraient la méthode d'ajustement du chapitre 5.

Pour la planification opérationnelle, les règles de gestion du chapitre 6 pourraient scinder les centrales dans l'ordre d'engagement. Cela rendrait probablement la gestion du parc plus efficace, tout en gardant la robustesse des règles de gestion.

En outre, le simulateur de règles du chapitre 6 pourrait être intégré dans un modèle de simulation-optimisation plus complexe, qui représenterait précisément d'autres aspects de la planification hydroélectrique : par exemple, les transactions sur le marché de l'énergie et la gestion du réseau électrique.

RÉFÉRENCES

Ahuja, Ravindra K. and Magnanti, Thomas L. and Orlin, James B. (1989). Chapter IV Network flows. *Handbooks in Operations Research and Management Science*, Elsevier, vol. 1. 211–369.

Amiri, Mohsen and Khanmohammadi, Sohrab (2013). A primary unit commitment approach with a modification process. *Applied Soft Computing*, *13*(2), 1007 – 1015.

Bacaud, Léonard and Lemaréchal, Claude and Renaud, Arnaud and Sagastizábal, Claudia (2001). Bundle Methods in Stochastic Optimal Power Management : A Disaggregated Approach Using Preconditioners. *Computational Optimization and Applications*, *20*(3), 227–244.

Bakken, B.H. and Bjorkvoll, T. (2002). Hydropower unit start-up costs. *Power Engineering Society Summer Meeting, 2002 IEEE*. vol. 3, 1522–1527 vol.3.

Baldwin, C. J. and Dale, K. M. and Dittrich, R. F. (1959). A Study of the Economic Shutdown of Generating Units in Daily Dispatch. *Transactions of the American Institute of Electrical Engineers. Part III : Power Apparatus and Systems*, *78*(4), 1272–1282.

Bellman, Richard Ernest and Dreyfus, Stuart E (1962). Applied dynamic programming. Rapport technique, Princeton University Press, New Jersey.

Belloni, A. and Lima, A.L. Diniz Souto and Maceira, M.E. Piñeiro and Sagastizábal, C.A. (2003). Bundle Relaxation and Primal Recovery in Unit Commitment Problems. The Brazilian Case. *Annals of Operations Research*, *120*(1-4), 21–44.

Bhardwaj, A. and Kamboj, V.K. and Shukla, V.K. and Singh, B. and Khurana, P. (2012). Unit commitment in electrical power system-a literature review. *Power Engineering and Optimization Conference (PEDCO) Melaka, Malaysia, 2012 Ieee International*. 275–280.

Boddy, Mark and Dean, Thomas L (1994). Deliberation scheduling for problem solving in time-constrained environments. *Artificial Intelligence*, *67*(2), 245–285.

Borghetti, A. and D'Ambrosio, C. and Lodi, A. and Martello, S. (2008). An MILP Approach for Short-Term Hydro Scheduling and Unit Commitment With Head-Dependent Reservoir. *Power Systems, IEEE Transactions on*, *23*(3), 1115–1124.

Borghetti, A. and Frangioni, A. and Lacalandra, F. and Lodi, A. and Martello, S. and Nucci, C.A. and Trebbi, A. (2001). Lagrangian relaxation and Tabu Search approaches for the unit commitment problem. *Power Tech Proceedings, 2001 IEEE Porto*. vol. 3, 1–7.

Breton, Michèle and Hachem, Saeb and Hammadia, Abdelghani (2002). A decomposition approach for the solution of the unit loading problem in hydroplants. *Automatica*, *38*(3), 477 – 485.

Carpentier, P. and Gohen, G. and Culioli, J.-C. and Renaud, A. (1996). Stochastic optimization of unit commitment : a new decomposition framework. *Power Systems, IEEE Transactions on*, *11*(2), 1067–1073.

Carpentier, P.-L. and Gendreau, M. and Bastin, F. (2013). Long-term management of a hydroelectric multireservoir system under uncertainty using the progressive hedging algorithm. *Water Resources Research*, *49*(5), 2812–2827.

Carpentier, P.-L. and Gendreau, M. and Bastin, F. (2015). Managing Hydroelectric Reservoirs Over an Extended Horizon Using Benders Decomposition With a Memory Loss Assumption. *Power Systems, IEEE Transactions on*, *30*(2), 563–572.

Catalão, J. P. S. and Pousinho, H. M. I. and Mendes, V. M. F. (2010). Mixed-integer nonlinear approach for the optimal scheduling of a head-dependent hydro chain. *Electric Power Systems Research*, *80*(8), 935 – 942.

Cerisola, Santiago and Baíllo, Álvaro and Fernández-López, José M. and Ramos, Andrés and Gollmer, Ralf (2009). Stochastic Power Generation Unit Commitment in Electricity Markets : A Novel Formulation and a Comparison of Solution Methods. *Operations Research*, *57*(1), 32–46.

Cheng, Chun-tian and Liao, Sheng-li and Tang, Zi-Tian and Zhao, Ming-yan (2009). Comparison of particle swarm optimization and dynamic programming for large scale hydro unit load dispatch. *Energy Conversion and Management*, *50*(12), 3007 – 3014.

Christoforidis, M. and Awobamise, B. and Frowd, Roderick J. and Rahimi, F.A. and Tong, S. and Aganagic, M. (1996). Short-term hydro generation and interchange contract scheduling for Swiss Rail. *Power Systems, IEEE Transactions on*, *11*(1), 274–280.

Conejo, A.J. and Arroyo, J.M. and Contreras, J. and Villamor, F.A. (2002). Self-scheduling of a hydro producer in a pool-based electricity market. *Power Systems, IEEE Transactions on*, *17*(4), 1265–1272.

CPLEX (2015). *CPLEX Optimizer ; release 12.6.2*. IBM ILOG.

CPLEX (2017). *CPLEX Optimizer ; release 12.7*. IBM ILOG.

Diniz, A.L. and Maceira, M. E P (2008). A Four-Dimensional Model of Hydro Generation for the Short-Term Hydrothermal Dispatch Problem Considering Head and Spillage Effects. *Power Systems, IEEE Transactions on*, *23*(3), 1298–1308.

Dorigo, M. and Birattari, M. and Stutzle, T. (2006). Ant colony optimization. *IEEE Computational Intelligence Magazine*, *1*(4), 28–39.

Dubost, L. and Gonzalez, R. and Lemaréchal, C. (2005). A primal-proximal heuristic applied to the French Unit-commitment problem. *Mathematical Programming*, *104*(1), 129–151.

Dupačová, J. and Gröwe-Kuska, N. and Römisch, W. (2003). Scenario reduction in stochastic programming. *Mathematical Programming*, *95*(3), 493–511.

Farhat, I. A. and El-Hawary, M. E. (2009). Optimization methods applied for solving the short-term hydrothermal coordination problem. *Electric Power Systems Research*, *79*(9), 1308 – 1320.

Ferreira, L. A F M (1992). Short-term scheduling of a pumped storage plant. *Generation, Transmission and Distribution, IEE Proceedings C*, *139*(6), 521–528.

Finardi, E.C. and da Silva, E.L. (2006). Solving the hydro unit commitment problem via dual decomposition and sequential quadratic programming. *Power Systems, IEEE Transactions on*, *21*(2), 835–844.

Finardi, Erlon Cristian and Scuzziato, Murilo Reolon (2014). A comparative analysis of different dual problems in the Lagrangian Relaxation context for solving the Hydro Unit Commitment problem. *Electric Power Systems Research*, *107*(0), 221 – 229.

Fleten, Stein-Erik and Haugstvedt, Daniel and Steinsbø, Jens Arne and Belsnes, Michael and Fleischmann, Franziska (2011). Bidding hydropower generation : Integrating short-and long-term scheduling. *17th Power System Computation Conference*. 1–8.

Fleten, Stein-Erik and Kristoffersen, Trine Krogh (2007). Stochastic programming for optimizing bidding strategies of a Nordic hydropower producer. *European Journal of Operational Research*, *181*(2), 916 – 928.

Fleten, Stein-Erik and Kristoffersen, Trine Krogh (2008). Short-term hydropower production planning by stochastic programming. *Computers & Operations Research*, *35*(8), 2656 – 2671. Queues in Practice.

Fosso, O. B. and Gjelsvik, A. and Haugstad, A. and Mo, B. and Wangensteen, I. (1999). Generation scheduling in a deregulated system. The Norwegian case. *IEEE Transactions on Power Systems*, *14*(1), 75–81.

Frangioni, Antonio (2002). Generalized Bundle Methods. *SIAM Journal on Optimization*, *13*(1), 117–156.

Frangioni, A and Gentile, C. and Lacalandra, F. (2009). Tighter Approximated MILP Formulations for Unit Commitment Problems. *Power Systems, IEEE Transactions on*, *24*(1), 105–113.

Frangioni, Antonio and Gentile, Claudio and Lacalandra, Fabrizio (2011). Sequential Lagrangian-MILP approaches for Unit Commitment problems. *International Journal of Electrical Power & Energy Systems*, *33*(3), 585 – 593.

Fu, Xiang and Li, Anqiang and Wang, Liping and Ji, Changming (2011). Short-term scheduling of cascade reservoirs using an immune algorithm-based particle swarm optimization. *Computers & Mathematics with Applications*, *62*(6), 2463 – 2471.

García-González, Javier and Parrilla, Ernesto and Mateo, Alicia (2007). Risk-averse profit-based optimal scheduling of a hydro-chain in the day-ahead electricity market. *European Journal of Operational Research*, *181*(3), 1354 – 1369.

Ge, Xiao-lin and Zhang, Li-zi and Shu, Jun and Xu, Nai-fan (2014). Short-term hydropower optimal scheduling considering the optimization of water time delay. *Electric Power Systems Research*, *110*(0), 188 – 197.

GENDREAU, M. et POTVIN, J.-Y., éditeurs (2010a). *Handbook of Metaheuristics*, vol. 146 de *International Series in Operations Research & Management Science*. Springer US, Boston, MA.

Gendreau, Michel and Potvin, Jean-Yves (2010b). Tabu Search. M. Gendreau et J.-Y. Potvin, éditeurs, *Handbook of Metaheuristics*, Springer US, vol. 146 de *International Series in Operations Research & Management Science*. 41–59.

Gil, E. and Bustos, J. and Rudnick, H. (2003). Short-term hydrothermal generation scheduling model using a genetic algorithm. *IEEE Transactions on Power Systems*, *18*(4), 1256–1264.

Glover, Fred (1986). Future paths for integer programming and links to artificial intelligence. *Computers & Operations Research*, *13*(5), 533 – 549. Applications of Integer Programming.

Glover, Fred (1989). Tabu Search - Part I. *ORSA Journal on Computing*, *1*(3), 190–206.

Glover, Fred (1990). Tabu Search - Part II. *ORSA Journal on Computing*, *2*(1), 4–32.

Guan, X. and Luh, P. B. and Yan, H. and Amalfi, J. A. (1992). An optimization-based method for unit commitment. *International Journal of Electrical Power & Energy Systems*, *14*(1), 9 – 17.

Gurobi (2015). *Gurobi Optimizer ; release 6.5*. Gurobi.

Hechme-Doukopoulos, Grace and Brignol-Charousset, Sandrine and Malick, Jérôme and Lemaréchal, Claude (2010). Integrated risk management of hydro power scheduling and contract management. *Power Systems, IEEE Transactions on*, *84*, 2–6.

Hedar, Abdel-Rahman and Ali, Ahmed Fouad (2012). Tabu search with multi-level neighborhood structures for high dimensional problems. *Applied Intelligence*, *37*(2), 189–206.

Heitsch, Holger and Römisch, Werner (2009). Scenario tree reduction for multistage stochastic programs. *Computational Management Science*, *6*(2), 117–133.

Hidalgo, Ieda G. and Correia, Paulo B. and Arnold, Francisco J. and Estrócio, João Paulo F. and de Barros, Regiane S. and Fernandes, Jéssica P. T. and Yeh, William W.-G. (2015). Hybrid Model for Short-Term Scheduling of Hydropower Systems. *Journal of Water Resources Planning and Management*, *141*(3), 04014062.

Holland, J. (1973). Genetic Algorithms and the Optimal Allocation of Trials. *SIAM Journal on Computing*, *2*(2), 88–105.

Hydro-Québec (2015). *Annual report 2015*. Hydro-Québec.

Hydro-Québec (2017). *Annual report 2017*. Hydro-Québec.

IEA (2017). *World Energy Statistics 2017*. IEA.

Johannesen, A and Gjelsvik, A and Fosso, O.B. and Flatabo, N. (1991). Optimal short term hydro scheduling including security constraints. *Power Systems, IEEE Transactions on*, *6*(2), 576–583.

Kargarian, A. and Fu, Yong and Li, Zuyi (2015). Distributed Security-Constrained Unit Commitment for Large-Scale Power Systems. *Power Systems, IEEE Transactions on*, *30*(4), 1925–1936.

Karimanzira, Divas (2016). Model Based Decision Support Systems. T. Rauschenbach, éditeur, *Modeling, Control and Optimization of Water Systems*, Springer Berlin Heidelberg, Berlin, Heidelberg. 185–220.

Karimanzira, Divas and Schwanenberg, Dirk and Allen, Christopher and Barton, Steven (2016). Short-Term Hydropower Optimization and Assessment of Operational Flexibility. *Journal of Water Resources Planning and Management*, *142*(2), 04015048.

Keutchayan, Julien and Gendreau, Michel and Saucier, Antoine (2017). Quality evaluation of scenario-tree generation methods for solving stochastic programming problems. *Computational Management Science*, *14*(3), 333–365.

Kirkpatrick, S. and Gelatt, C. D. and Vecchi, M. P. (1983). Optimization by Simulated Annealing. *Science*, *220*(4598), 671–680.

Labadie, J. (2004). Optimal Operation of Multireservoir Systems : State-of-the-Art Review. *Journal of Water Resources Planning and Management*, *130*(2), 93–111.

Ladurantaye, Daniel De and Gendreau, Michel and Potvin, Jean-Yves (2009). Optimizing profits from hydroelectricity production. *Computers & Operations Research*, *36*(2), 499 – 529. Scheduling for Modern Manufacturing, Logistics, and Supply Chains.

Lemaréchal, Claude (2001). Lagrangian Relaxation. M. Jünger et D. Naddef, éditeurs, *Computational Combinatorial Optimization*, Springer Berlin Heidelberg, vol. 2241 de *Lecture Notes in Computer Science*. 112–156.

Lemaréchal, C. and Sagastizábal, C. and Pellegrino, F. and Renaud, A. (1996). Bundle methods applied to the unit-commitment problem. J. Doležal et J. Fidler, éditeurs, *System Modelling and Optimization*, Springer US, IFIP — The International Federation for Information Processing. 395–402.

Liang, Ruey-Hsun (1997). Application of grey linear programming to short-term hydro scheduling. *Electric Power Systems Research*, *41*(3), 159 – 165.

Liang, Ruey-Hsun (2000). A noise annealing neural network for hydroelectric generation scheduling with pumped-storage units. *Power Systems, IEEE Transactions on*, *15*(3), 1008–1013.

Liang, R.-H. and Hsu, Y-Y (1996). Short-term hydro-scheduling using Hopfield neural network. *Generation, Transmission and Distribution, IEE Proceedings-*, *143*(3), 269–275.

Liu, Cong and Shahidehpour, M. and Wu, Lei (2010). Extended Benders Decomposition for Two-Stage SCUC. *Power Systems, IEEE Transactions on*, *25*(2), 1192–1194.

Liu, G. and Tomsovic, K. (2015). Robust unit commitment considering uncertain demand response. *Electric Power Systems Research*, *119*(0), 126 – 137.

Maceira, ME Pineiro and Terry, Leslie A and Costa, F Serra and Damázio, J Machado and Melo, ACG (2002). Chain of optimization models for setting the energy dispatch and spot price in the Brazilian system. *Proceedings of the Power System Computation Conference-PSCC*. vol. 2, 24–28.

Mahor, Amita and Rangnekar, Saroj (2012). Short term generation scheduling of cascaded hydro electric system using novel self adaptive inertia weight PSO. *International Journal of Electrical Power & Energy Systems*, *34*(1), 1 – 9.

Mantawy, A.H. and Abdel-Magid, Y.L. and Selim, S.Z. (1998). Unit commitment by tabu search. *Generation, Transmission and Distribution, IEE Proceedings-*, *145*(1), 56–64.

Marchand, Alexia and Gendreau, Michel and Blais, Marko and Emiel, Grégory (2018a). An Efficient Tabu Search Procedure for Short-Term Planning of Large-Scale Hydropower Systems.

Marchand, Alexia and Gendreau, Michel and Blais, Marko and Emiel, Grégory (2018b). Fast Near-Optimal Heuristic for the Short-Term Hydro-Generation Planning Problem. *IEEE Transactions on Power Systems*, *33*(1), 227–235.

Marchand, Alexia and Gendreau, Michel and Blais, Marko and Emiel, Grégory (2018c). Optimized operating rules for short-term hydropower planning in a stochastic environment.

Mohammadi-ivatloo, B. and Zareipour, H. and Amjady, N. and Ehsan, M. (2013). Application of information-gap decision theory to risk-constrained self-scheduling of GenCos. *Power Systems, IEEE Transactions on*, *28*(2), 1093–1102.

Moradi, Saeed and Khanmohammadi, Sohrab and Hagh, Mehrdad Tarafdar and Mohammadi-ivatloo, Behnam (2015). A semi-analytical non-iterative primary approach based on priority list to solve unit commitment problem. *Energy*, *88*(0), –.

Naresh, R. and Sharma, J. (2002). Short term hydro scheduling using two-phase neural network. *International Journal of Electrical Power & Energy Systems*, *24*(7), 583 – 590.

Ongsakul, W. and Petcharaks, N. (2004). Unit commitment by enhanced adaptive Lagrangian relaxation. *Power Systems, IEEE Transactions on*, *19*(1), 620–628.

Osorio, GJ and Matias, JCO and Catalao, JPS (2013). A review of short-term hydro scheduling tools. *Power Engineering Conference (UPEC), 2013 48th International Universities'*. IEEE, 1–6.

Parrilla, Ernesto and García-González, Javier (2006). Improving the B&B search for large-scale hydrothermal weekly scheduling problems. *International Journal of Electrical Power & Energy Systems*, *28*(5), 339 – 348.

Piekutowski, M.R. and Litwinowicz, T. and Frowd, R. (1993). Optimal short-term scheduling for a large-scale cascaded hydro system. *Power Industry Computer Application Conference, 1993. Conference Proceedings*. 292–298.

Pousinho, H.M.I. and Mendes, V.M.F. and Catalao, J.P.S. (2011). Profit-based head-dependent short-term hydro scheduling considering risk constraints. *PowerTech, 2011 IEEE Trondheim*. 1–6.

Pursimo, J. M. and Antila, H. K. and Vilkko, M. K. and Lautala, P. A. (1998). A short-term scheduling for a hydropower plant chain. *International Journal of Electrical Power & Energy Systems*, *20*(8), 525 – 532.

Pérez-Díaz, Juan I. and Wilhelmi, José R. and Arévalo, Luis A. (2010). Optimal short-term operation schedule of a hydropower plant in a competitive electricity market. *Energy Conversion and Management*, *51*(12), 2955 – 2966.

Quan, Ran and Jian, Jinbao and Yang, Linfeng (2015). An improved priority list and neighborhood search method for unit commitment. *International Journal of Electrical Power & Energy Systems*, *67*(0), 278 – 285.

Rockafellar, R. T. and Wets, Roger J.-B. (1991). Scenarios and Policy Aggregation in Optimization Under Uncertainty. *Mathematics of Operations Research*, *16*(1), 119–147.

Sagastizábal, C. (2012). Divide to conquer : decomposition methods for energy optimization. *Mathematical Programming*, *134*(1), 187–222.

Sampaio, G.S. and Saraiva, J.T. and Sousa, J.C. and Mendes, V.T. (2013). Optimization of the operation of hydro stations in market environment using Genetic Algorithms. *European Energy Market (EEM), 2013 10th International Conference on the*. 1–8.

Saravanan, B. and Das, Siddharth and Sikri, Surbhi and Kothari, D.P. (2013a). A solution to the unit commitment problem - a review. *Frontiers in Energy*, *7*(2), 223–236.

Saravanan, B. and Sikri, S. and Swarup, K.S. and Kothari, D.P. (2013b). Unit commitment using DP - An exhaustive working of both classical and stochastic approach. *Power, Energy and Control (ICPEC), 2013 International Conference on*. 382–385.

SAS (2015). *SAS/OR ; release 14.1*. SAS.

Seguin, S. and Cote, P. and Audet, C. (2016). Self-Scheduling Short-Term Unit Commitment and Loading Problem. *Power Systems, IEEE Transactions on*, *31*(1), 133–142.

Seki, T. and Yamashita, N. and Kawamoto, K. (2010). New Local Search Methods for Improving the Lagrangian-Relaxation-Based Unit Commitment Solution. *Power Systems, IEEE Transactions on*, *25*(1), 272–283.

Senjyu, T. and Shimabukuro, K. and Uezato, K. and Funabashi, T. (2003). A fast technique for unit commitment problem by extended priority list. *Power Systems, IEEE Transactions on*, *18*(2), 882–888.

Shawwash, Ziad K and Siu, Thomas K and Russell, SO Denis (2000). The BC Hydro short term hydro scheduling optimization model. *Power Systems, IEEE Transactions on*, *15*(3), 1125–1131.

Simopoulos, D.N. and Kavatza, S.D. and Vournas, C.D. (2006). Unit commitment by an enhanced simulated annealing algorithm. *Power Systems, IEEE Transactions on*, *21*(1), 68–76.

Séguin, Sara and Fleten, Stein-Erik and Côté, Pascal and Pichler, Alois and Audet, Charles (2017). Stochastic short-term hydropower planning with inflow scenario trees. *European Journal of Operational Research*, *259*(3), 1156 – 1168.

Tahanan, Milad and van Ackooij, Wim and Frangioni, Antonio and Lacalandra, Fabrizio (2015). Large-scale Unit Commitment under uncertainty. *4OR*, *13*(2), 115–171.

Takigawa, F.Y.K. and Finardi, E.C. and da Silva, E.L. (2010). A decomposition strategy to solve the Short-Term Hydrothermal Scheduling based on Lagrangian Relaxation. *Transmission and Distribution Conference and Exposition : Latin America (T D-LA), 2010 IEEE/PES*. 681–688.

Taktak, Raouia and D'Ambrosio, Claudia (2017). An overview on mathematical programming approaches for the deterministic unit commitment problem in hydro valleys. *Energy Systems*, *8*(1), 57–79.

Ton-That, Quoc-Anh and Falcon, Thérèse and Blais, Marko and Gendreau, Michel (2014). Implicit Dynamic Programming approach for the optimization of hydroelectric systems. Rapport technique, Hydro-Québec Production, CIRRELT.

van Ackooij, Wim and Henrion, René and Möller, Andris and Zorgati, Riadh (2014). Joint chance constrained programming for hydro reservoir management. *Optimization and Engineering*, *15*(2), 509–531.

van Ackooij, Wim and Lopez, Irene Danti and Frangioni, Antonio and Lacalandra, Fabrizio and Tahanan, Milad (2018). Large-scale unit commitment under uncertainty : an updated literature survey. Rapport technique, Università di Pisa.

Vardanyan, Y. and Amelin, M. (2011). The state-of-the-art of the short term hydro power planning with large amount of wind power in the system. *Energy Market (EEM), 2011 8th International Conference on the European*. 448–454.

Vardanyan, Yelena and Amelin, Mikael and Hesamzadeh, Mohammad (2013). Short-term hydropower planning with uncertain wind power production. *Power and Energy Society General Meeting (PES), 2013 IEEE*. IEEE, 1–5.

Wang, Jinwen (2009). Short-term generation scheduling model of Fujian hydro system. *Energy Conversion and Management*, *50*(4), 1085 – 1094.

Wu, Lei (2013). An Improved Decomposition Framework for Accelerating LSF and BD Based Methods for Network-Constrained UC Problems. *Power Systems, IEEE Transactions on*, *28*(4), 3977–3986.

Wu, Lei and Shahidehpour, M. and Li, Zuyi (2012). Comparison of Scenario-Based and Interval Optimization Approaches to Stochastic SCUC. *Power Systems, IEEE Transactions on*, *27*(2), 913–921.

Yang, Kan and Zheng, Jiao and Yang, Min and Zhou, Ran and Liu, Guoshuai (2013). Adaptive Genetic Algorithm for Daily Optimal Operation of Cascade Reservoirs and its Improvement Strategy. *Water Resources Management*, *27*(12), 4209–4235.

Zheng, Q.P. and Wang, J. and Liu, A.L. (2015). Stochastic Optimization for Unit Commitment–A Review. *Power Systems, IEEE Transactions on*, *30*(4), 1913–1924.

Zorgati, Riadh and van Ackooij, Wim (2011). Optimizing financial and physical assets with chance-constrained programming in the electrical industry. *Optimization and Engineering*, *12*(1-2), 237–255.